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Timo Mitze

Empirical Modelling in Regional Science

Towards a Global Time–Space–Structural Analysis

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Dr. Timo Mitze
Rheinisch-Westfälisches Institut für
Wirtschaftsforschung
Essen, Germany

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Für Karla, Anna Luisa und Jonathan.

In großer Dankbarkeit an meine Eltern.

In Erinnerung an Nina.

Preface

This research has started back in 2006 as an attempt to improve the practice of regional macroeconometric modelling with a particular focus on German data. I hope that the research results produced over the last years and presented in this book are of some value for its readers and may serve as a starting point for discussion and elaboration of further research ideas. Throughout the conduct of my research, I have realized that an ideal working process would need to rely on a recursive modelling strategy, which is able to incorporate findings from one part of the research also in the other parts. Unfortunately, doing so was not always feasible. At certain points, I simply had to make a cut, for the work not to become a never-ending story. This means that there are still open ends that need to be tied together in future work. It also literally taught me that knowledge creation in science is a continuous flow. And—although it may be frustrating from time to time—it is simply a great pleasure to be a part of it.

Without the support of many people this dissertation probably would not have come that far. In first place, I want to thank my doctoral supervisor Prof. Dr. Helmut Karl for his continuous support over the last years. Moreover, I would like to thank Prof. Dr. Manfred Lösch and Prof. Dr. Christoph M. Schmidt for their careful guidance and advice on how to handle empirical problems and improve this work. I am also grateful for valuable comments from Prof. Dr. Jesus Mur and Prof. Dr. Jean Paelinck, whose work in spatial econometrics inspired me to do own research in the field. And, of course, I would like to thank my co-authors Björn Alecke, Janina Reinkowski and Gerhard Untiedt for discussing research ideas, getting problems solved and my time schedule organized. Thanks so much, it was a pleasure to work with you and I hope we continue to do so. My colleagues at the RWI, Alfredo Paloyo and Arndt Reichert, were a great support as well—both in proof-reading earlier drafts and giving me an excellent preparation for my final dissertation defense. Moreover, I would like to thank Philipp Breidenbach, Rosemarie Gülker, Saskia Schmidt, Joel Stiebale, Matthias Vorell, Simeon Vosen and various colleagues at national and international conferences for their relevant feedback and advice. I also acknowledge financial support from the Evangelisches Studienwerk Villigst e.V., which helped me to conduct large parts of the research presented in this book.

Finally, there is my family. For sure, without their support I would not have made it. My wife Karla and my parents supported me so much throughout all the ups and downs over the last years. I am incredibly happy about this. My kids Anna Luisa and Jonathan helped me to stay with both feet solid on the ground and were a source of joy and happiness, when I needed new inspiration for my work. I dedicate this book to them.

Essen, Germany Timo Mitze

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Chapter 1
Introduction and Outline

1.1 State of the Art in Regional Econometric Modelling

Economic agents interact in structural relationships through time and in space. This work starts from the empirical observation that all three dimensions, namely time, space, and structural functional forms, are important for an integrative framework of modern empirical analysis in regional science. While the notion of space is integral to research in regional science, adequate empirical tools such as modern methods in spatial statistics and spatial econometrics that allow for sound statistical inference in a regression framework have only been developed within the last years. The research field of spatial econometrics initially evolved as a critical reflection of Paelinck (1973) about what contemporary regional econometrics and model building was neglecting at that time. Paelinck also hinted at two essential factors needed in order to correctly capture the spatial dynamics of the economy: (i) the relative location of the regions concerned and (ii) the intraregional location of activities.[1]

A more elaborate vision of what the research agenda of spatial econometrics could be, was then first expressed in Paelinck's General Address to the Dutch Statistical Association's Annual Meeting 1974 in Tilburg. This research agenda was composed of five key principles: (i) definition of topological variables, (ii) handling of spatial interdependence and (iii) spatial asymmetry, both relevant for characterizing economic interactions, (iv) the concept of "allotopy" as a measure of influence for the distance to exogenous variables and (v) modelling choice problems in space.[2] What followed was a "stormy evolution" (Sarafoglu and Paelinck 2008) with a rapidly growing number of methodological and applied contributions. By now, spatial econometrics is becoming a mainstream tool in economics, geography, and regional science. Although considerable progress has been made, however, there are still many open challenges. The recent contributions of LeSage and Pace (2009) as well as Elhorst (2010) have clearly shown that the interpretation of re-

[1] A detailed historical tracking of the synthesis of spatial econometrics is given by Sarafoglu and Paelinck (2008).

[2] These five principles are also exhaustively discussed in Ancot et al. (1990).

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gression coefficients from spatial econometric models is not as straightforward as regional scientists have thought so in the recent past. Elhorst (2010) calls it illustratively "raising the bar", that is, only in these days, the spatial econometrics research agenda has passed an important threshold in terms of model specification, application, and interpretation.

Next, regional scientists have become aware that a better understanding of causes and consequences of many regional economic phenomena requires a structural analysis, which ideally starts from a fully specified model, well-grounded in theory (see Holmes 2010). This would allow properly addressing relevant issues of endogeneity, causality and simultaneity in regional modelling and policy analysis. Having a long history in dealing with these concepts, modern macroeconomic theory and macroeconometric practice may therefore be a good source of inspiration for regional scientists. As Rickman (2010) points out in his contribution to the 50 year anniversary volume of the *Journal of Regional Science*, one way to go ahead is using the macroeconometric approach to construct structural models for regional policy analysis as an alternative to traditional, merely descriptive tools in regional science.[3] Besides recent advantages in dynamic general equilibrium modelling, macroeconomic theory offers a broad econometric toolkit for modelling dynamic processes over time. Following the influential work of Sims (1980), the use of vector autoregressive (VAR) models has become a widespread empirical tool complementary to dynamic single equation specifications. The VAR approach starts from the general treatment of variables as being endogenous in a system of interdependent equations and grounds specification issues such as (weak) exogeneity of variables and the direction of causality on empirical testing. Only recently, VAR models have come to the focus of regional modelling with a first application by Carlino and DeFina (1999).

For macroeconometric methods to be applied, tools are needed that are able to link time- and space-related analysis in a unified framework. In this setting, econometric practice has greatly benefited from recent advances in the analysis of panel data, which enables researchers to track cross sectional units over time. When the evolution of spatial econometrics can be described as "stormy", the use of methods for panel data analysis in econometrics is best comparable to a hurricane since the pioneering papers by Kuh (1959), Mundlak and Hoch (1965) and Balestra and Nerlove (1967) among others. The benefits from panel data are manifold. Most of them can be attributed to its greater capacity for capturing the complexity of human behavior compared to single cross-section or time-series data (see Hsiao 2007). An important advantage is thus the ability to construct and test more complicated behavioral hypotheses including, e.g., distinguishing among structural homogeneity versus heterogeneity for different (sub-)groups of the sample over time. Tests for the poolability of the data and slope homogeneity are likely to increase the efficiency of estimation and allow identifying structural differences in the data. Moreover, panel data methods are able to control for the impact of omitted time-invariant variables,

[3] With "descriptive" being defined in line with Holmes (2010) as a type of explorative empirical analysis, able to identify correlations of variables but not causal effects. The latter would need either a structuralist- or experimentalist-modelling approach.

as well as uncovering dynamic relationships. By now, there is a huge literature on the latter, being able to spell out the importance of time-adjustment processes for economic variables, both in stationary as well as non-stationary data settings.[4]

In this context, a highly innovative subfield of research aims at linking the dynamic panel time-series approach with spatial econometric tools. First contributions have already hinted at the potential power of such time–space combinations. Beenstock and Felsenstein (2010), for instance, analyze, by means of panel data with a long time dimension, the importance of spatial interrelationships for the evolution of a system of long-run cointegrated variables over time. The authors show that, next to local ("within" panel) cointegration as stable co-movement of variables for each cross-section (typically regions) over time, spatial lags for each particular variable, computed as a weighted average of observations from cross-sections in geographical proximity, may provide important information to ensure the stability of the time-series cointegration relationship. The latter calls for a wider concept of global cointegration as being composed of "within" (the typical times-series type) and "between" panel cointegration. Additionally, Di Giacinto (2010), among others, has demonstrated the potential use of spatial vector autoregressive (SpVAR) models, in particular for the computation of space–time impulse responses as a tool to summarize the information conveyed by regional dynamic multipliers to account for the simultaneity and two-way causality in modelling economic variables with an explicit role for spatial spillovers.

There are numerous further examples of the fruitful interaction between mainstream (time series, panel) and spatial econometrics. An illustrative one is Vaona (2009, 2010). In his contributions, the author shows how to adapt familiar time-series tools to the field of spatial econometrics, such as the Ramsey (1969) RESET statistic to disentangle model misspecifications of unknown form, which potentially lead to spurious spatial correlation in the model residuals. Together with related work on spatial model testing strategies, such as Florax et al. (2003), or the application of spatial J-type tests for model comparison (Kelejian 2008; Burridge and Fingleton 2010), these efforts reflect the recognition of the need of statistical guidance for empirical model validation strategies also in spatial econometrics, which is a long-standing practice in the field of time-series econometrics. Similar arguments hold for the concept of (Granger) causality, which has only recently been adapted to the field of spatial econometrics by Herrera et al. (2010). The other way around, panel time series econometrics has benefited from the consideration of spatial interdependence in the design of (second generation) panel unit root and cointegration tests (see, e.g., Baltagi et al. 2007).

Although the above examples show that significant progress has been made, it still seems to be a long way until empirical models that fully account for the structural, temporal and spatial interrelatedness of regional economic systems are applicable. This, of course, is due to the inherent complexity of a global space–time–structural approach, which can approximately be described by Fig. 1.1. The best way to tackle these challenges is to start from a stylized framework for global analysis, which we will briefly discuss in the next section.

[4]For a comprehensive overview see, for instance, Arellano (2003).

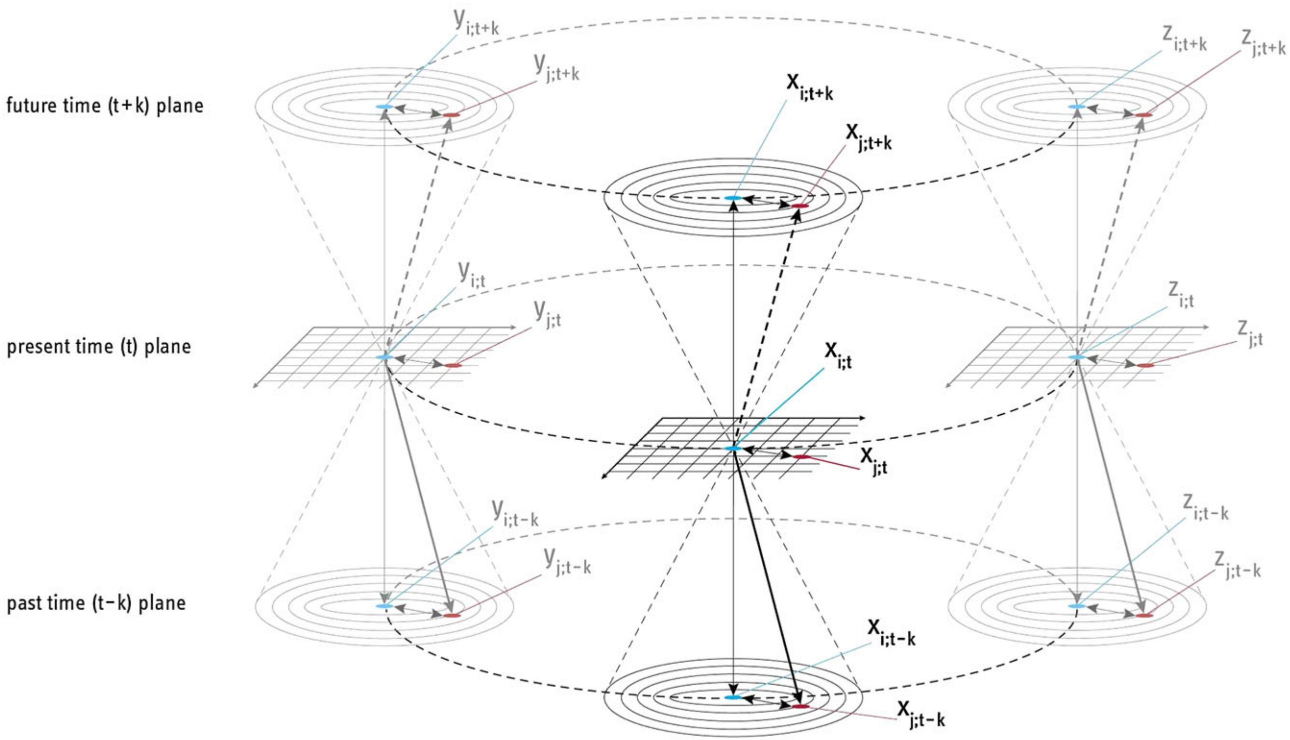

Fig. 1.1 Space–time relationships among variables in a structural modelling framework. *Source*: Own figure in extension to the single variable presentation in Haggett et al. (1977)

1.2 A Stylized Framework for Time–Space–Structural Analysis

The perception that the task of empirical regional science is to unravel the complex global pattern of autocorrelation both in space and time has already been expressed in early contributions to the field, such as Cliff and Ord (1981). The best way to map such time–space–structural relationships is to start from a graphical presentation. Figure 1.1 highlights the mutual relationships for the set of three variables X, Y and Z. The figure is inherently multidimensional. First, it relates past $(t-k)$, present (t) and future $(t+k)$ values for each variable in the typical concept of temporal autoregressive processes. In addition, we assume that the time interval between our data recording points is sufficiently long compared to the rate of operation of geographical processes, so that what appear as simultaneous effects between cross-sections (regions) i and j may occur.

The simultaneous effects for each time plane represent a pure spatial autoregressive mechanism. As the figure shows, for each variable, there are also general space–time covariances, indicating that future and/or past values for cross-section j may be correlated with the present value of the variable for cross-section i and so on. Besides, different structural relationships through space and time have to be modelled between the three variables, either in a contemporaneous way (as highlighted in Fig. 1.1), or as more general cross-variable time–space covariances.[5]

The relationship between the variables can also be stated in a mathematical, system of equations, way. Keeping the stylized model as simple as possible, we assume a linear (or log-linearized) relationship among the variables and rule out future information as determinant for the current value. Then, in its most general form, the system covering the dependence of each variable across past time and space, as well as the systematic two-way causal relationships among them can be written as

$$\begin{aligned}X_{i,t} &= \sum_{k=1}^{K} \alpha 1_{i,k} X_{i,t-k} + \sum_{k=0}^{K} \alpha 2_{i,k} Y_{i,t-k} + \sum_{k=0}^{K} \alpha 3_{i,k} Z_{i,t-k} \\ &\quad + \sum_{k=0}^{K} \alpha 4_{i,k} X^{*}_{i,t-k} + \sum_{k=0}^{K} \alpha 5_{i,k} Y^{*}_{i,t-k} + \sum_{k=0}^{K} \alpha 6_{i,k} Z^{*}_{i,t-k} + u1_{i,t}, \qquad (1.1)\end{aligned}$$

$$\begin{aligned}Y_{i,t} &= \sum_{k=0}^{K} \beta 1_{i,k} X_{i,t-k} + \sum_{k=1}^{K} \beta 2_{i,k} Y_{i,t-k} + \sum_{k=0}^{K} \beta 3_{i,k} Z_{i,t-k} \\ &\quad + \sum_{k=0}^{K} \beta 4_{i,k} X^{*}_{i,t-k} + \sum_{k=0}^{K} \beta 5_{i,k} Y^{*}_{i,t-k} + \sum_{k=0}^{K} \beta 6_{i,k} Z^{*}_{i,t-k} + u2_{i,t}, \qquad (1.2)\end{aligned}$$

[5] The reader has to note that no attempt was made to draw all possible connections for cross-sectional observations for each variable over time, since this would simply overburden the graphical presentation in Fig. 1.1.

$$Z_{i,t} = \sum_{k=0}^{K} \gamma 1_{i,k} X_{i,t-k} + \sum_{k=0}^{K} \gamma 2_{i,k} Y_{i,t-k} + \sum_{k=1}^{K} \gamma 3_{i,k} Z_{i,t-k}$$
$$+ \sum_{k=0}^{K} \gamma 4_{i,k} X^*_{i,t-k} + \sum_{k=0}^{K} \gamma 5_{i,k} Y^*_{i,t-k} + \sum_{k=0}^{K} \gamma 6_{i,k} Z^*_{i,t-k} + u3_{i,t}, \quad (1.3)$$

where $i = 1, \dots, N$ are cross-sectional units with reference to points or regions in space, t is the time dimension, $\alpha 1, \dots, \alpha 3$; $\beta 1, \dots, \beta 3$; $\gamma 1, \dots, \gamma 3$ are regression coefficients and $u1_{i,t}$, $u2_{i,t}$, $u3_{i,t}$ are the residuals for each equation and $k = 0, \dots, K$ denotes the maximum length of the time lags considered. In panel data settings the error term is typically composed of an unobserved individual time-fixed effect μ_i and a remainder time-varying error component $\nu_{i,t}$ so that $u_{i,t} = \mu_i + \nu_{i,t}$.[6] Both variables are assumed to have zero means and a constant variance as $\mu_i \sim N(0, \sigma^2_\mu)$ and $\nu_{i,t} \sim N(0, \sigma^2_\mu)$. Moreover, linear independence of the error components is assumed as $\mathrm{Cov}(\mu_i, \nu_{i,t}) = 0$.

The asterisked variables in (1.1)–(1.3) refer to spatialized versions of X, Y and Z defined as:

$$X^*_{i,t} = \sum_{j \neq i}^{N} w_{ij} X_{jt}, \quad (1.4)$$

$$Y^*_{i,t} = \sum_{j \neq i}^{N} w_{ij} Y_{jt}, \quad (1.5)$$

$$Z^*_{i,t} = \sum_{j \neq i}^{N} w_{ij} Z_{jt}, \quad (1.6)$$

where w_{ij} are the elements of a spatial weighting matrix W with $i, j = 1, \dots N$. The term $\sum_{j \neq i}^{N} w_{ij} X_{jt}$ is also called the spatial lag of variable X since it represents a linear combination of values from X constructed from observations (regions) that neighbor observation i. There are different ways to specify the spatial weighting scheme W, including common borders, distances, or other forms of geographical and economic linkages. As Elhorst (2010) puts it, the choice of W may, in fact, be a delicate choice in empirical practice.

From an empirical modeler's point of view, estimating the system of (1.1)–(1.3) bears several challenges, of which endogeneity and simultaneity among the relations are surely the most demanding ones. Also, the inherent time–space simultaneity in (1.1)–(1.3) has to be addressed, together with general reflections about consistency and efficiency of the parameter estimates for different combinations of N and T.

Research on panel econometrics has made considerable progress to give advice on most of these points. One general merit of the panel econometric approach, besides accounting for omitted variables through the inclusion of the unobservable

[6] Additionally, one may start from a two-way specification and include time-fixed effects as well.

time fixed effects μ_i, is the increase in estimation efficiency by pooling the data over the cross-sectional units N. The latter gains however only hold if the parameter restrictions in terms of slope homogeneity for cross-sections are valid as $\alpha 1_1 = \alpha 1_2 = \cdots = \alpha 1_N$ (and likewise for all other coefficients). Otherwise, pooling the data leads to inconsistent estimates. Given the availability of panel data with increasing T, one possibility is then to start from an unrestricted individual coefficient model and test for the poolability for the whole set of cross-sections or different sub-groups.[7] This may give important insights regarding the similarity for spatially referenced cross-sections when testing the validity of certain functional forms for the estimated model.

Another important feature of (1.1)–(1.3) is its time-dynamic specification, which relates observations for each variable to own past values. In panel data settings, the estimation of dynamic specifications is not straightforward given the correlation of the lagged endogenous variable with the error term of the model. In the recent literature, different estimators have been proposed that typically start from first differencing the model to eliminate the unobservable individual effects from the model. However, there still appears the problem that the transformed error term is correlated with the transformed lagged dependent variable and thus needs to be instrumented. In a seminal paper, Anderson and Hsiao (1981) recommend to use twice-lagged levels or first differences to serve as valid instruments. Subsequently, the estimation technique has been refined by the GMM approaches in Arellano and Bond (1991) as well as Blundell and Bond (1998). Besides estimating the transformed model in first differences, the latter estimator jointly estimates a stacked dataset in first differences as well as levels simultaneously. For the latter, the Blundell–Bond estimator employs information in first differences to instrument the lagged endogenous variable.

Given the availability of easy-to-apply estimators, IV/GMM approaches to dynamic panel data settings are by now a common tool in empirical economics and regional science. This likewise holds for the estimation of spatial econometric models as shown, e.g., by Kelejian and Prucha (1998) for the general cross-sectional case. In spatio-temporal data settings, Fingleton and Le Gallo (2008) have recently shown that GMM estimators developed for dynamic panel data are, for instance, also extremely useful in instrumenting further endogenous right-hand-side variables such as the spatial lag. This further indicates the advancing integration of both strands of the literature. Right-hand-side endogeneity in turn is quite likely to occur in empirical applications, given the impact of measurement errors, omitted variables, or the existence of an unknown set of simultaneous structural equations.

The latter argument is an important point. A simultaneous equation approach may be necessary in order to account for endogeneity and causality among variables, as well as interdependence of the model's error terms. In extension to the standard (single-equation) assumption about the error terms, this requires that the likely non-zero covariance matrices for the error components as $\Sigma_\mu = [\sigma^2_{\mu_{(l,k)}}]$ (with

[7] Of course, taking the incidental parameter problem into account (Neyman and Scott 1948), although the latter is more severe for the non-linear case.

$l = 1, \ldots, 3$, $k = 1, \ldots, 3$) and $\Sigma_\nu = [\sigma^2_{\nu(l,k)}]$ are taken into account. Here, the literature for panel data is still in its infancy to setup structural- or time-series-model-based full-information solutions.

The same holds for the joint inclusion of time and spatial lags of the endogenous variable in one unifying framework as shown in (1.1)–(1.3). First experimental estimation approaches nevertheless point to the merits of this modelling direction.[8] Similar arguments also apply for the inclusion of further spatial lags for the explanatory variables of the dynamic system in (1.1)–(1.3). The latter opens up the modelling space from a spatial lag framework to a more general class of spatial Durbin type models, which may be seen as an adequate general starting point to test for a parsimonious version of the equation system.[9]

Finally, for panels with increasing T, the time series properties of the variables also turn out to be essential for empirical estimation. Only for the case of a stable co-movement of X, Y and Z over time, the system can be estimated in its original form. Otherwise, the risk of running spurious regressions is present. While the standard time-series definition of cointegration "within" each cross-sectional unit over time has been widely recognized in empirical modelling based on the seminal work of Engle and Granger (1987), the importance of "between" panel cointegration for spatially referenced data is in most cases left unexplored. This calls for a global concept of cointegration analysis.

1.3 Contribution of This Work

1.3.1 General Outline

In this work, I take up the research topics outlined above, aiming to push forward the research frontier in empirical regional science step by step. Most of the topics dealt with start from a concrete empirical problem, while problem solving also aims at generating some new knowledge in a methodological way, e.g. by the complementary use of Monte Carlo simulation studies. The work is structured in three parts, addressing major issues in building up a stylized regional economic model. All empirical applications used in this work use German regional data, mostly at the federal state level.[10] Thus, the results may help in improving the empirical fit of regional econometric and calibration models for Germany as, e.g., the HERMIN framework which is widely used for policy analysis.[11] While regional econometric models for a long time have been merely down-scaled versions of national models, renewed

[8]See, e.g., Bouayad-Agha and Vedrine (2010).

[9]The spatial Durbin model was first discussed in Anselin (1988).

[10]Data sources are given in each chapter. The datasets can also be obtained from the author upon request.

[11]For a description of the HERMIN model see, e.g., Bradley et al. (2001).

interest in the field has shown that a proper modelling framework needs to explicitly incorporate the specific needs of a time–space–structural approach. The MASST model is a good example of this latter type of modelling philosophy.[12] Local resource endowments, interregional factor movements (both capital and labor) and spatial spillovers have to be taken into account at the regional level, besides those standard supply- and demand-mechanisms at work in modern macroeconometric models. In the following, I present the outline and main results of my empirical research with three headings: (i) internal migration and the labor market, (ii) trade and FDI activity of German regions, and (iii) growth, factor and final demand modelling.

1.3.2 Internal Migration and the Labor Market

Part I deals with the role of internal migration as an important adjustment mechanism for regional labor market imbalances. The interplay between internal migration and regional labor market performance has for long been in the focus of economic policy making. A central question to address is to what extent regional disparities in real wages, income, and unemployment can be balanced through labor migration as an equilibrating force. This work also looks at the feedback effects potentially arising from the migration response. Investigating such two-way interdependencies, Chap. 2 directly starts from a simultaneous treatment of migration and labor market signals in a Panel VAR approach for German states between 1991 and 2006. One goal is to estimate a benchmark model which is able to predict labor market related changes in the region's net in-migration rate and vice versa. Moreover, a further focus of the analysis is to track the evolution of the particular East–West migration since re-unification, aiming to shed more light on the East German "empirical puzzle" characterized by lower migration responses than expected from the East German regional labor market position relative to the West.

Indeed we get evidence for such a puzzle throughout the mid-1990s, which is likely to be caused by huge West–East income transfers, a fast exogenously driven wage convergence, and the possibility of East–West commuting. However, we also observe an inversion of this relationship for subsequent periods. That is, along with a second wave of East–West movements around 2001, net flows out of East Germany were much higher than expected after controlling for its weak labor market and macroeconomic performance. Since this second wave is also accompanied by a gradual fading out of economic distortions and a downward adjustment of expectations about the speed of East–West convergence in standard of livings, this supports the view of "repressed" migration flows for that period. Towards the sample end in 2006, structural differences between the two macro regions turn out to be insignificant, indicating that migratory movements between East and West Germany react in a similar way to regional labor market signals. This latter result may be taken as a first hint for the advancing labor market integration between the two macro regions.

[12] See Capello (2007) and Capello et al. (2008) for an overview.

Chapters 3 and 4 look at the migration equation in a single equation context more carefully by accounting for the role of age-group specific heterogeneity and spatial dependency in migration flows, respectively. The analysis in Chap. 3 thereby takes a regionally disaggregated view for 97 Spatial Planning Regions between 1996–2006 and tests the labor market implications of the neoclassical migration model for five different age groups (18 to 25, 25 to 30, 30 to 50, 50 to 65, and over 65 years). Empirical support is found for the main transmission channels identified by the neoclassical framework, while the impact of labor market signals is tested to be of greatest magnitude for workforce relevant age-groups and especially young cohorts from 18 to 25 and 25 to 30 years. The results of the standard neoclassical migration model remain stable if commuting flows, the regional human capital endowment, the region's international competitiveness as well as differences in the settlement structure are added as further explanatory variables. These results underline the prominent role played by labor market conditions in determining internal migration rates of the working population in Germany.

Chapter 4 analyzes the role of network interdependencies in a dynamic panel data model for German internal migration flows since re-unification. In the context of this chapter, network dependencies are associated with correlations of migration flows strictly attributable to proximate flows in geographic space. So far, a capacious account of spatial patterns in German migration data is still missing in the empirical literature. The analysis starts with the construction of spatial weighting matrices for the analyzed system of interregional flow data and applies spatial regression techniques to properly handle the underlying space–time interrelations. Besides spatial extensions to commonly used dynamic panel data estimators based on the spatial lag and unconstrained spatial Durbin model, spatial filtering techniques are also applied. When combining both approaches to a mixed spatial-filtering-regression specification, the resulting model performs remarkably well in terms of capturing spatial dependence in the migration equation, and at the same time the combination of different techniques qualifies the model to pass essential IV diagnostic tests. The basic message for future research is that space–time dynamics is highly relevant for modelling German internal migration flows.

1.3.3 Link to the World: Trade & FDI Activity

Part II deals with an analysis of trade and foreign direct investment at the regional scale as important variables to link regional economic systems with the world economy. Chapter 5 specifies a four-equation system for exports, imports, inward and outward FDI of German states with EU27 countries between 1993 and 2005 in a gravity-type framework. The latter is a common empirical vehicle in the new trade literature and new economic geography, which accounts explicitly for the role of space in the specification of trading costs. By using a simultaneous equation approach for panel data, the resulting empirical specification is also able to control for the underlying structural interrelation of these variables as either being substitutive or complementary in nature after controlling for common factors both influencing trade and FDI activity (such as market potential, the region's international competitiveness, and so on).

Starting from the aggregate perspective, the analysis supports earlier empirical evidence for Germany finding substitutive linkages between trade and outward FDI. The latter may be motivated with the alternative choice options that firms in a specific region face when serving foreign markets. Switching to the (macro-)regional perspective, we get further insights. For example, splitting the sample to isolate West German to EU27 trade-FDI linkages, the revealed variable correlations closely follow the predictions from new trade theory models, where export replacement effects of FDI are again operating. However, at the same time, outward FDI are found to stimulate trade via reverse goods imports. On the contrary, for the East German economy, we mainly get substitutive linkages when looking at EU wide trade and FDI. This regional heterogeneity found in our estimation results thus emphasizes the need to explicitly take into account the regional dimension in the analysis of cross-variable linkages between trade and FDI.

Chapter 6 backs up the empirical analysis in Chap. 5 by running a small Monte Carlo simulation study to investigate which panel data estimation approach is best equipped to estimate gravity-type models assigning a prominent role to time-fixed, space related variables such as the geographical distance between trading partners. We compare the performance of IV and non-IV approaches in the presence of time-fixed variables and right-hand-side endogeneity (e.g., the correlation of the distance variable with the error term of the model in the presence of other time-invariant omitted variables which are correlated with the former), where we explicitly control for the problem of IV selection in Hausman–Taylor (HT) type models. The HT model is the benchmark approach in estimating panel data sets with both time-varying and time-fixed regressors.

The simulation results show that the HT model with perfect knowledge about the underlying data structure (instrument orthogonality) has, on average, the smallest bias. However, compared to the empirically relevant specification with imperfect knowledge and instruments chosen by statistical criteria, simple non-IV rival estimators based on extensions of the fixed effects model (FEM), such as the fixed effects vector decomposition (FEVD) as two-step estimator, perform equally well or even better. We illustrate these findings by estimating gravity-type models for German regional export activity within the EU. The results show that the HT specification is likely to get upward biased results for the crucial trade costs variable proxied by geographical distances.

Chapter 7 then adapts the global cointegration approach of Beenstock and Felsenstein (2010) to analyze the role of variables measuring the internationalization activity (trade and FDI) for output determination. The analysis shows that for German regions, neighboring effects are indeed important to track the long- and short-run evolution of output driven by trade and FDI for (West) German state level data during the period 1976 to 2005. We apply various homogeneous and heterogeneous panel data estimators for a Spatial Panel Error Correction Model (SpECM) of regional output growth. For the long-run cointegration equation, the empirical results support the hypothesis of export- and FDI-led growth. We also show that export and outward FDI activities may exhibit positive cross-regional effects, giving rise to the notion of global cointegration. In the short run SpECM specification, direct and indirect spatial externalities are also highly present. As a sensitivity analysis, we use a spatial weighting matrix based on interregional goods transport flows rather than geographical distances. This scheme thus allows us to address soundly the role of trade/FDI enhancing as well as substitutive effects for a system of interconnected regions. We account for the potential endogeneity problem of the latter approach by using historical data for intra-German transportation flows prior to the sample period.

1.3.4 Growth, Factor and Final Demand

While Chapter 7 in Part II already puts the focus on output allocation via internationalization activity, in Part III, the relationship between output and factor as well as final demand is analyzed more in-depth. Chapter 8 starts with an analysis of the finite sample properties of different estimators for dynamic panel data models in a simultaneous equation context. We provide new results for the multiple equation case of dynamic panel data models by testing different system-extensions for standard fixed effects-type models as well as familiar IV/GMM-style estimators, which have recently been proposed in the literature. Since the notion of simultaneity arises for many economic relationships, it is important to analyze the finite sample performance of multiple equation estimators for panel data. Here, empirical guidance in the panel econometric literature is still missing.

In the context of this chapter, the most competitive estimators from the Monte Carlo simulation exercise are then applied to an analysis of the role of public and private capital accumulation on regional output growth among German states for the sample period 1991–2006. On the one hand the model is used to identify the likely two-way effects among the variables as, e.g., postulated by the hypothesis of q-complementary among private and public investments, on the other hand the model is applied to conduct a regional policy analysis. For the latter purpose the baseline model is augmented by variables measuring interregional spillover effects from public capital as well as transfer payments from regional equalization schemes. We find positively directed but insignificant effects from interregional spillovers in transport infrastructure, while spillovers from science infrastructure even tend to be negative. The latter result is likely to originate from specific locational advantages of science infrastructure, which allows regions to poach production factors from its neighborhood. For regional equalization transfers, we find mixed results, crucially depending on the specific policy program.

Chapter 9 further looks at output growth driven by regional policy instruments. The analysis particularly seeks to reveal the direct and indirect regional impacts of a large-scale capital investment support scheme, the so called "Joint Task for the Improvement of Regional Economic Structures" (GRW), on labor productivity growth for 225 German labor market regions between 1994 and 2006. Using a neoclassical growth-model framework, we test for the policy impact on the speed of convergence to the long-run steady-state income. Our empirical specification is perfectly in line with the spirit of neoclassical growth theory, in which even a permanent increase in the physical investment rate may only exhibit a temporary effect on productivity growth, leaving the long-run growth rate unaffected.

The results reveal a significant positive direct effect of the regional policy instrument on labor productivity growth, with the speed of convergence being almost doubled for supported regions half way below their steady-state compared to the case of not being supported. In order to check for the robustness of the results, we also augment the standard regression approach by spatial econometric elements. The Inclusion spatial lags of the regressand and right-hand-side regressors in the convergence equation shows that, besides the direct positive effect of the GRW investment support scheme, there is a negative spillover effect from the policy stimulus to neighboring regions. The latter effect may be explained by the increased attractiveness of the supported region, which is able to poach capital investments and other input factors from neighboring regions. Though, on average, the indirect effect results in a slowdown in the speed of adjustment to the steady-state income, the net effect of GRW support to lagging regions is still positive for the analyzed sample period.

Chapter 10 of this work then looks at the role played by income (fluctuations) in determining long- and short-run regional consumption functions for different samples of German states between 1970 and 2007. A particular focus is set on the analysis of homogeneity versus heterogeneity in the individual regional adjustment processes of consumption in consequence to current income changes. Knowing more about the type of spatial response to policy changes may be seen as a further important field for future analysis in regional science. In particular, using a habit-formation augmented model for the Permanent Income Hypothesis, the empirical analysis in this chapter tests the significance and quantitative size of "excess sensitivity" in consumption adjustment to predictable income shocks. The latter may reflect liquidity constraints, myopic behavior or loss aversions. However, our results do not give strong empirical support for these phenomena. In the short-run approach past and current income changes turn out to be insignificant if we control for potentially omitted variables (in particular, for a long West German sample between 1970 and 2007, we get mixed results for a sample comprising all German states from 1991 onwards). Although we find income sensitivity in the specified Panel Error Correction Model (ECM) approach integrating the short- and long-run perspective, this share is found to be smaller than recently reported by other scholars based on German regional data.

By testing for slope homogeneity in the dynamic consumption model, we are able to identify regional asymmetries in the adjustment path due to income shocks. We finally also account for the likely role of spatial autocorrelation when dealing with regional data. The results for spatially filtered variables show that the estimated structural coefficients remain stable after filtering has been done and turn out to be even more in line with the predictions of neoclassical consumption theory. That is, after controlling for the likely role of external habit formation in addition to internal habit persistence, the share of excess sensitivity gets even smaller. This also raises doubts about whether current income changes are an effective measure for excess income sensitivity as typically used in the traditional empirical literature since they may simple capture the effects of omitted variables. Moreover, full poolability of the data is not rejected for the spatially filtered model. This allows us to estimate an aggregate German dynamic consumption function since re-unification with the following characteristics: Real income and consumption are cointegrated in the long-run, the speed of adjustment from short-run deviations to the long-run equilibrium is about 20–30% per year. The share of excess sensitivity to income changes is rather small.

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Part I
Internal Migration and the Labor Market

Chapter 2
A Panel VAR Approach for Internal Migration Modelling and Regional Labor Market Dynamics in Germany

2.1 Introduction

Given the rather low mobility rates for EU member states compared to the US and Australia, the extent to which regional disparities in real wages, income, and unemployment can be balanced through labor migration is a subject of obvious interest for economic policy (see, e.g., Bonin et al. 2008). According to mainstream neoclassical theory the link between migration and regional labor market variables is assumed to work as follows: Regions with relatively high unemployment and low wage levels should experience net out-migration into regions with better employment opportunities. A rising number of available jobs in the target region as well as a decline in job opportunities in the home region then ensure that the regional labor market disparities will disappear over time. In the long-run cross-regional labor market equilibrium unemployment differences can then only be explained by differences in regional wage levels as compensation for the higher unemployment risks, while otherwise factor prices are assumed to equalize across regions.[1]

Taking up this research question, we aim at analyzing whether and by what magnitude regional differences in wage levels, unemployment among other economic (push and pull) factors significantly influence the internal migratory behavior within

[1] See Siebert (1994) for a similar line of argumentation for regional labor market dynamics in Germany. A critical view of this concept of compensating differentials is given by Blanchflower and Oswald (1994, 2005), who introduce a wage-curve linking low wage levels and high unemployment rates for a particular region. Recent empirical studies by Wagner (1994), Baltagi and Blien (1998) and Baltagi et al. (2007) indeed give evidence for a wage-curve relationship in Germany.

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Jointly with Björn Alecke and Gerhard Untiedt. Björn Alecke, Gesellschaft für Finanz- und Regionalanalysen (GEFRA), e-mail: Alecke@gefra-muenster.de; Gerhard Untiedt, GEFRA & Technical University Clausthal, e-mail: Untiedt@gefra-muenster.de.

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Germany. We put a particular emphasis on the analysis of the West and East German labor market integration since re-unification and investigate the likely two-way interdependences among migration and labor market variables. For empirical estimation we use internal migration flows between the German federal states (NUTS1 level) between 1991 and 2006 and apply dynamic panel data methods in a VAR context.

The remainder of the chapter is organized as follows. In the next section, we present a short literature review. Section 2.3 sketches the underlying theoretical model that will serve as a starting point in specifying testable empirical specifications for estimation. Section 2.4 gives a short overview of the data used for the empirical analysis including a discussion of the time series properties. Section 2.5 describes the Panel VAR (PVAR) approach; Sect. 2.6 reports the estimation results. In Sect. 2.7, we test the explanatory power of the PVAR for predicting interregional East–West migration flows since re-unification and take a look at the East German "empirical puzzle". Section 2.8 finally concludes the chapter.

2.2 Literature Review

This literature review mainly serves two purposes. First, from a partial equilibrium perspective we look at recent empirical contributions in specifying a stable long-run (neoclassical) migration equation. Second, using this long-run migration equation as an important building block for a more profound labor market analysis, we then augment the scope of the literature review to multiple equation approaches, which account more carefully for dynamic feedback effects among migration and labor market variables.

Given the huge body of literature on the neoclassical migration model, it is not surprising that the empirical results for the long-run migration equation are somewhat mixed and country specific. Focusing on empirical evidence for Germany, Decressin (1994) examines gross flows for West German states between 1977 and 1988. His results show that a wage increase in one region relative to others causes a disproportional rise in the gross migration flows in the first region, while a rise in the unemployment rate for a region relative to others disproportionally lowers the gross flows. However, the author does not find a significant link between bilateral gross migration and regional differences in wage level or unemployment when purely cross-sectional estimates are considered. Difficulties in proving a significant influence of regional wage decreases on the migratory behavior within Germany are also found in earlier empirical studies based on micro-data to motivate individual migratory behavior in Germany. Among these are Hatzius (1994) for West Germany, as well as Schwarze and Wagner (1992), Wagner (1992), Burda (1993) and Büchel and Schwarze (1994) for the East German states. Subsequent micro studies mainly focused on qualifying the theoretically unsatisfactory result with respect to wage rates. Schwarze (1996) for example shows that by using the expected rather than actual wage rate the results turn significant. The latter is also confirmed in Brücker and Trübswetter (2004) focusing on the role of self-selection in East–West migration.

Opposed to this earlier evidence, recent macroeconomic studies assign a more prominent role to regional wage rate differentials in predicting German internal migration flows. Parikh and Van Leuvensteijn (2003) use the core neoclassical migration model with regional wage and unemployment differentials as driving forces for interregional migration augmented by additional indicators such as regional housing costs, geographical distance and inequality measures. For the short sample period 1993–1995, the authors find a significant non-linear relationship between disaggregated regional wage rate differences and East–West migration, while unemployment differences are found to be insignificant. Hunt (2000) and Burda and Hunt (2001) analogously identify wage rate differentials and particularly the closing gap in regional differences driven by a fast East–West convergence as a powerful indicator in explaining observed state-to-state migration patterns. Using data up to the late 1990s, Burda and Hunt (2001) find that the decline in East–West migration starting from 1992 onwards can almost exclusively be explained by wage differentials and the fast East–West wage convergence, while unemployment differences do not seem to play an important part in explaining actual migration trends.[2]

So far, we have looked at single equation (partial equilibrium) approaches to estimate a stable long-run neoclassical migration equation. Building on this literature there is also a bulk of studies extending the scope of the analysis to a multiple equation setting in order to account more carefully for the likely feedback effects of migratory movements on labor market variables and their joint responses to shocks. Aiming to control for two-way effects has resulted in a variety of empirical specifications, either from a structural (see e.g. Okun 1968; Muth 1971; Salvatore 1980; Bilger et al. 1991, and the large literature following Carlino and Mills 1987) or time-series perspective (see Blanchard and Katz 1992; Decressin and Fatas 1995; Möller 1995; Lu 2001; Mäki-Arvela 2003, or Partridge and Rickman 2006). The latter approach typically applies Vector Autoregression (VAR) models, which provide a valuable tool for analyzing the dynamics of economic processes. In particular the VAR approach is well suited to analyze regional adjustment processes in reaction to exogenous (macroeconomic) shocks. A general discussion of labor market analysis with VAR models is for instance given in Summers (2000).

To our knowledge, the only empirical application of a system approach of migration and labor market dynamics for German regions is given by Möller (1995). Using a VAR model for seven West German regions between 1960 and 1993 the author mainly finds the theoretically expected negative response of net in-migration to a one standard deviation shock in unemployment with a time-lag of about two to three years. The analysis of the impulse–response functions also shows that the unemployment shock on migration is likely to have a negative long-run impact on

[2]When interpreting these findings, one however has to bear in mind that the above cited studies exclusively use data until the mid/late-1990s, which in fact may bias the results with respect to the wage component, given the fast (politically driven) East–West wage convergence as one overriding trend in the overall pattern of East German macroeconomic development. In the second half of the 1990s, wage convergence substantially lost pace, so that the estimated link may become less stable when extending the sample period beyond the mid-1990s.

regional population levels, which in turn bring back the unemployment rate to its old steady state level. Contrary to the predictions of the neoclassical migration model, Möller (1995) finds that migration is negatively affected by a regional wage rate increase. The author explains this latter result in terms of a reduced factor demand for labor given the change in the relative price for capital and labor input, which then overcompensates the positive initial signal of a wage rate increase to the internal and external labor market forces.

The feedback effects of labor market variables to migration shocks largely show a negative mid- to long-run impact for wages, labor productivity and labor participation. Möller (1995) takes the VAR findings that shocks are on average only gradually absorbed with full adjustment being achieved in decades rather than years in support for the existence of regional hysteresis effects. Finding appropriate answers on the latter point has already inspired empirical research since the seminal contribution of Blanchard and Katz (1992). In a similar VAR setup for Finnish regions, Mäki-Arvela (2003), for instance, gets empirical results closely related to those obtained in Möller (1995).

2.3 Modelling Migration in a System of Regional Labor Market Dynamics and Economic Development

In this section we briefly describe the neoclassical migration model and integrate the specification into a stylized framework of labor market dynamics and regional evolutions in the spirit of the Blanchard and Katz (1992) approach. One important distinction from the latter is that we explicitly include a long-run migration equation in our model rather than capturing it residually.[3] Mainstream economic literature offers different theories trying to explain the reasons for people moving from one region to another, which can broadly be classified as either being micro or macro oriented (see Stillwell 2005, and Etzo 2008, for recent surveys). Within the latter category, the neoclassical framework—modelling an individual's lifetime expected income (utility) maximization approach—clearly takes an outstanding role (see e.g. Maza and Villaverde 2004).

Harris and Todaro (1970) set up a neoclassical model that centers around the concept of expected income, which—for staying in the region of residence (E_{ii})—is defined as a function of the real wage rate in region i (W_i) and the probability of being employed ($PROB_i$). The latter in turn is a function of unemployment rate in region i (UR_i) and a set of potential variables related both to economic and non-economic factors (S_i). The same set of variables, with different subscripts for region

[3]Blanchard and Katz (1992) set up a three-equation model including employment minus unemployment changes, the employment to labor force ratio as well as the labor force to population ratio as endogenous variables. From the behavior of these variables over time, the authors are able compute the effect on the unemployment and the participation rate as well as the implied effect on net out-migration, e.g., as response to a reduction in employment.

j accordingly, is also used to model the expected income from moving to the alternative (destination) region. Taking also a set of economic (house prices, transfer payments, etc.) and non-economic costs (such as region specific amenities), as well as costs of moving from region i to j into account (C_{ij}), the individual's decision will be made in favor of moving to region j if

$$E_{ii} \leq E_{ij} - C_{ij}, \tag{2.1}$$

with $E_{ii} = f(PROB_i[UR_i, S_i], W_i)$ and $E_{ij} = f(PROB_j[UR_j, S_j], W_j)$. This shows that at the core of the Harris–Todaro model the agent weighs the wage level in the home (origin) and target (destination) region with the individual probability of finding employment. We are then able to set up a model for the regional net migration (NM_{ij}), which is defined as regional gross in-migration flows to i from j net of outflows from i to j as

$$NM_{ij} = f(W_i, W_j, UR_i, UR_j, S_i, S_j, C_{ij}). \tag{2.2}$$

With respect to the theoretically motivated sign of the explanatory variables, we expect that an increase in the home country's real wage rate (or alternatively, income level) *ceteris paribus* leads to higher net migration inflows, while a real wage rate increase in region j results in a decrease of the net migration rate. On the contrary, an increase in the unemployment rate in region i (j) has negative (positive) effects on the bilateral net migration from i to j. Costs of moving from i to j are typically expected to be an impediment to migration and thus are negatively correlated with net migration.

For empirical modelling purposes, we operationalize the set of additional variables (S_i, S_j) that may work as pull or push factors for regional migration flows in the following way. Given that migration flows have a long-run structural rather than just business cycle perspective; one likely determinant of migration flows is real labor productivity growth. As Coulombe (2006) argues, the transmission channel from labor productivity to migration is closely linked to the convergence concept of the (new) growth literature: Under the assumption of absolute convergence migration flows are assumed to react to different initial levels of labor productivity in two regions i and j. Gradually, the gap between the two regions will be eliminated in the catching-up process and structural migration between i and j will decrease smoothly in a time horizon that however goes well beyond the business-cycle horizon. Conditional convergence is necessarily associated with other structural differences captured in S_i and S_j so that the initial gap in labor productivities may not be fully closed, however the basic correlation between changes in labor productivity and net in-migration should hold as well until the regions have not fully converged to their respective long run steady state levels.[4]

[4]However, as McCann (2001) argues, regional economic growth is a complex process and may, for instance, be strongly influenced by the location decision of firms, which in turn gives rise to potential regional scale effects e.g. via agglomeration forces. Such forces then may act as a pull factor for migration so that also a positive correlation between productivity growth and net in-migration could be in order rather than the expected negative one from the standard growth model.

From the viewpoint of the conditional convergence assumption of the new growth theory, one key factor driving differences in the long run steady-state labor productivity level is the regional endowment with human capital. Hence, the link between migration and regional human capital may be of great importance, e.g., in analyzing the causes and consequences for a regional 'brain drain' associated with a sharp decline in the regional skill composition due to net out-migration. In the microeconomic literature, the link between the formal skill level of the prospect migrant and the actual migration decision is already well-documented, where recent contributions typically establish a positive correlation between individual qualification and mobility (see, e.g., Borjas 1987 for a theoretical discussion, and Wolff 2006, as well as Bode and Zwing 2008, for an overview of empirical studies for Germany).[5]

At the empirical level, typically a log-linear form of the stylized migration equation in (2.2) is chosen, which may either include contemporaneous and/or lagged values for the explanatory and also endogenous variable. As suggested by Puhani (2001), the latter lag structure accounts for likely time delays in the transmission process of labor market signals to migration flows. The inclusion of lagged terms for the endogenous variable reflects different channels through which past flows may affect current migration such as communication links between migrants and friends and relatives left behind. The latter linkage in turn may influence prospective migrants who want to live in an area where they share cultural and social backgrounds with other residents (see Chun 1996, for a detailed discussion). Finally, we restrict the explanatory variables to enter as inter-regional differences yielding a triple-indexed model specification (ij, t), where ij denote the difference between region i and region j and t is the time index. Allowing for a general lag structure the migration equation may be written as:

$$\begin{aligned} nm_{ij,t} = \gamma_{10} + \gamma_{11}(L)nm_{ij,t-1} + \gamma_{12}(L)\widetilde{wr}_{ij,t-1} + \gamma_{13}(L)\widetilde{ur}_{ij,t-1} \\ + \gamma_{14}(L)\widetilde{ylr}_{ij,t-1} + \gamma_{15}(L)\tilde{q}_{ij,t-1} + \gamma_{16}(L)\widetilde{hc}_{ij,t-1} + e_{ij,t}, \quad (2.3) \end{aligned}$$

where $\tilde{x}_{ij,t}$ for any variable $x_{ij,t}$ is defined as $\tilde{x}_{ij,t} = (x_{i,t} - x_{j,t})$ and (L) is the lag operator. The error term $e_{ij,t} = \mu_{ij} + \nu_{ij,t}$ is assumed to have the typical one-way error component structure including time-fixed individual effects and a remainder error term. Next to the core labor market variables as real wage $(\widetilde{wr})$ and unemployment rate differences $(\widetilde{ur})$, we include changes in real labor productivity $(\Delta\widetilde{ylr})$, the labor participation rate $(\tilde{q})$, and an index for human capital $(\widetilde{hc})$ as control variables in S_{ij}.

Equation (2.3) is frequently used in a partial equilibrium framework in order to estimate the elasticity of migratory movements with respect to labor market and further (macro)economic variables. However, as Gallin (1999) points out, this type of analysis can be misleading because migration and labor market conditions are

[5]One pitfall at the empirical level is to find an appropriate proxy for the regional human capital endowment (see, e.g., Dreger et al. 2008, as well as Ragnitz 2007, for a special focus on East–West differences). We therefore test different proxies in form of a composite indicator based on the regional human capital potential (high school and university graduates), the skill level of employee as well as innovative activities such as regional patent intensities.

usually jointly determined. To do so, we set up a small-scale model for regional labor market and economic development, which closely follows the specification in Möller (1995). Centering around the neoclassical migration equation with regional differences in the unemployment and real wage rate as explanatory variables, the author includes a set of behavioral equations derived from an eclectic model of regional evolutions first proposed by Blanchard and Katz (1992).[6] We use a similar equation system of the following form:

$$\begin{aligned}\widetilde{wr}_{ij,t} &= \gamma_{20} + \gamma_{21}(L)nm_{ij,t-1} + \gamma_{22}(L)\widetilde{wr}_{ij,t-1} + \gamma_{23}(L)\widetilde{ur}_{ij,t-1}\\ &\quad + \gamma_{24}(L)\Delta\widetilde{ylr}_{ij,t-1} + \gamma_{25}(L)\tilde{q}_{ij,t-1} + \gamma_{26}(L)\widetilde{hc}_{ij,t-1} + e_{ij,t},\end{aligned} \tag{2.4}$$

$$\begin{aligned}\widetilde{ur}_{ij,t} &= \gamma_{30} + \gamma_{31}(L)nm_{ij,t-1} + \gamma_{32}(L)\widetilde{wr}_{ij,t-1} + \gamma_{33}(L)\widetilde{ur}_{ij,t-1}\\ &\quad + \gamma_{34}(L)\Delta\widetilde{ylr}_{ij,t-1} + \gamma_{35}(L)\tilde{q}_{ij,t-1} + \gamma_{36}(L)\widetilde{hc}_{ij,t-1} + e_{ij,t},\end{aligned} \tag{2.5}$$

$$\begin{aligned}\Delta\widetilde{ylr}_{ij,t} &= \gamma_{40} + \gamma_{41}(L)nm_{ij,t-1} + \gamma_{42}(L)\widetilde{wr}_{ij,t-1} + \gamma_{43}(L)\widetilde{ur}_{ij,t-1}\\ &\quad + \gamma_{44}(L)\Delta\widetilde{ylr}_{ij,t-1} + \gamma_{45}(L)\tilde{q}_{ij,t-1} + \gamma_{46}(L)\widetilde{hc}_{ij,t-1} + e_{ij,t},\end{aligned} \tag{2.6}$$

$$\begin{aligned}\tilde{q}_{ij,t} &= \gamma_{50} + \gamma_{51}(L)nm_{ij,t-1} + \gamma_{52}(L)\widetilde{wr}_{ij,t-1} + \gamma_{53}(L)\widetilde{ur}_{ij,t-1}\\ &\quad + \gamma_{54}(L)\Delta\widetilde{ylr}_{ij,t-1} + \gamma_{55}(L)\tilde{q}_{ij,t-1} + \gamma_{56}(L)\widetilde{hc}_{ij,t-1} + e_{ij,t},\end{aligned} \tag{2.7}$$

$$\begin{aligned}\widetilde{hc}_{ij,t} &= \gamma_{60} + \gamma_{61}(L)nm_{ij,t-1} + \gamma_{62}(L)\widetilde{wr}_{ij,t-1} + \gamma_{63}(L)\widetilde{ur}_{ij,t-1}\\ &\quad + \gamma_{64}(L)\Delta\widetilde{ylr}_{ij,t-1} + \gamma_{65}(L)\tilde{q}_{ij,t-1} + \gamma_{66}(L)\widetilde{hc}_{ij,t-1} + e_{ij,t},\end{aligned} \tag{2.8}$$

There are different ways to put theoretically motivated sign restrictions on the variable coefficients of the system in (2.4)–(2.8).[7] However, our empirical strategy deliberately rests on an eclectic modelling strategy to first select theoretical motivated variables and thereafter use a flexible VAR approach for estimation. This strategy relaxes (arbitrary) theoretical restrictions put on right-hand-side variables and lets the data determine whether migration has equilibrating or disequilibrating effects on the labor market and, e.g., whether a 'wage' or 'Phillips' curve may be in order for the wage equation in the system. We will give a discussion of the specification and estimations issues of the Panel VAR (PVAR) approach in the following. However, before that we first briefly describe the data base used for estimation and discuss the time series properties of the variables in the next section. The latter in fact may have important implications for the selection of appropriate estimation techniques in the context of dynamic panel data models.

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[6]The approach in Möller (1995) defines regional differences for region i relative to the rest of the country aggregate j.

[7]A discussion of theoretical motivated coefficient signs in (2.4)–(2.8) is given in an extended working paper version. See Alecke et al. (2009).

2.4 Data and Stylized Facts of Intra-German Migration

For empirical estimation we use data for the 16 German states between 1991 and 2006. We model migration based on inter-regional migration flow data (disregarding within-state flows with a total of $N \times (N-1) \times T = 16 \times 15 \times 16 = 3840$ observations) rather than aggregating state level net migration relative to the rest of the country (that is, summed over all regions minus region i). The former strategy gives us more degrees of freedom for estimation and avoids an artificial averaging of migration flows. Though we use population rather than labor force migration, we assume that both variables are highly correlated and that the former may serve as a proxy for the latter. All economic variables are denoted in real terms. That is, we account explicitly for the evolution of regional differences in price levels. Such data is typically ignored in empirical analysis given its scare evidence at an intra-country perspective. Here we use data compiled by Roos (2006) based on prices indices for 50 German cities in 1993 and construct a time series of regional price levels by using state level inflations rates for consumer prices between 1991 and 2006. Since differences in regional price levels may offset or even increase regional wage rate differentials, an explicit account for regional (consumer) prices in estimating migration flows seems promising. A full description of the data sources is given in Table 2.1.

Looking at selected stylized facts, in particular the evolution of East–West migration flows since re-unification deserves attention. Figure 2.1 plots state level net in-migration rates between 1991 and 2006. Additionally, Fig. 2.2 reports aggregated migration flows for the two East–West macro regions, which allows to identify distinct waves in macro regional migration over time.[8] As Fig. 2.1 shows, West German states benefit on average from the net out-migration trend of Eastern states. The only outlier among the West German states is Lower Saxony. However, the latter trend in its internal migration flows is largely exogenously driven by German resettlers from abroad.[9] For empirical estimation, we will explicitly control for the latter exogenously induced migration effect, which does not bear much economic interpretation. Taking a closer look at the evolution of state level net migration rates for East Germany, only Brandenburg has a positive migration balance throughout the 1990s benefiting from its geographical proximity to Berlin. The time series pattern of other East German states is persistently negative over the whole sample period. If we aggregate the inter-regional state level flows to gross and net out-migration among the two macro regions West and East (including Berlin), Fig. 2.2 allows to identify the two waves of East–West net outflows with peaks in the early 1990s and around 2001. Compared to this, West to East migratory flows have been rather stable (and much lower) over time.

[8] East Germany including Berlin.

[9] The explanation is that these resettlers are legally obliged to first move to the central base Friesland in Lower Saxony and then only subsequently can freely migrate to other states within Germany.

Table 2.1 Data description and source

Variable	Description	Source
$outm_{ijt}$	Total number of out-migration from region i to j	Destatis (2008a)
inm_{ijt}	Total number of in-migration from region i to j	Destatis (2008a)
$y_{i(j)t}$	Gross domestic product in region i and j respectively	VGRdL (2008)
$py_{i(j)t}$	GDP deflator in region i and j respectively	VGRdL (2008)
$ylr_{i(j)t}$	Real labor productivity defined as $(yl_{j,t} - py_{j,t})$	VGRdL (2008)
$pop_{i(j)t}$	Population in region i and j respectively	VGRdL (2008)
$emp_{i(j)t}$	Total employment in region i and j respectively	VGRdL (2008)
$unemp_{i(j)t}$	Total unemployment in region i and j respectively	VGRdL (2008)
$ur_{i(j)t}$	Unemployment rate in region i and j respectively defined as $(unemp_{i,t} - emp_{i,t})$	VGRdL (2008)
$pcpi_{i(j)t}$	Consumer price index in region i and j respectively based on Roos (2006) and regional CPI inflation rates	Roos (2006), RWI (2009)
$wr_{i(j)t}$	Real wage rate in region i and j respectively defined as wage compensation per employee deflated by $pcpi_{i(j)t}$	VGRdL (2008)
$q_{i(j)t}$	Labor market participation rate in region i and j respectively defined as $(emp_{i,t} - pop_{i,t})$	VGRdL (2008)
$hc_{i(j)t}$	Human capital index as weighted average of: 1) high school graduates with university qualification per total population between 18–20 years (*hcschool*), 2) number of university degrees per total population between 25–30 years (*hcuni*), 3) share of employed persons with a university degree relative to total employment (*hcsvh*), 4) number of patents per pop. (*hcpat*)	Destatis (2008b, 2008c), Federal Employment Agency (2009), DPMA (2008)

Note: All variables in logs. For Bremen, Hamburg and Schleswig-Holstein no consumer price inflation rates are available. We took the West German aggregate for these states, this also accounts for Rhineland-Palatine and Saarland until 1995

Since we are dealing with macroeconomic time series, the (non)-stationarity of the data and thus spurious regression may be an issue. We therefore perform the Im–Pesaran–Shin (2003) panel unit root tests for the variables in the system of equation. Optimal lag length is chosen according to the Akaike information criterion (AIC). The results are shown in Table 2.2. In all cases the IPS test rejects the null hypothesis of non-stationarity. These results are broadly in line with our theoretical expectations concerning the order of integration of the variables: Migration and labor market variables (unemployment rate, labor participation rate etc.) are typically assumed to be stationary processes and the same accounts for labor productivity (growth). Human capital endowment is likewise expected to change only gradually over time. These results give us a high level of flexibility in terms of employing different dynamic panel data (DPD) estimators both in levels and first differences as typically proposed in the recent literature.

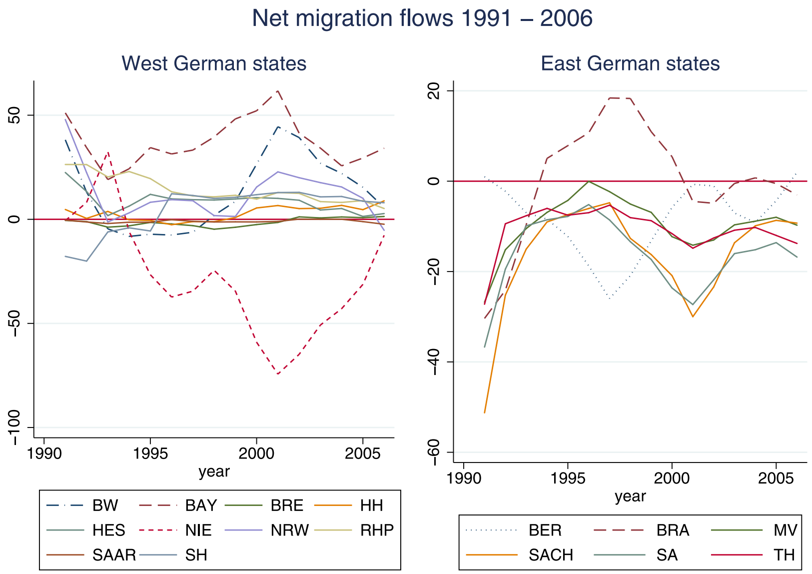
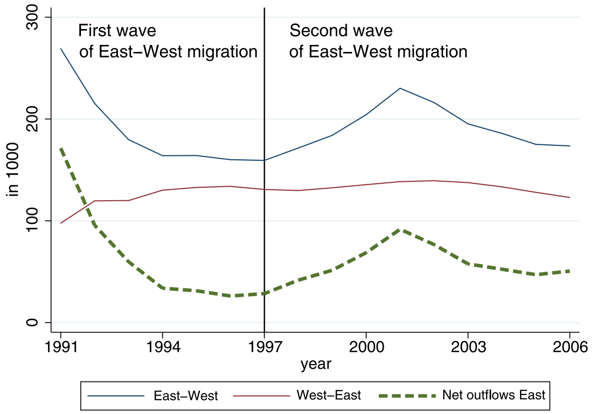


Fig. 2.1 Time series plots for German state level net migration between 1991 and 2006. *Note*: BW = Baden-Württemberg, BAY = Bavaria, BER = Berlin, BRA = Brandenburg, BRE = Bremen, HH = Hamburg, HES = Hessen, MV = Mecklenburg-Vorpommern, NIE = Lower Saxony, NRW = North Rhine-Westphalia, RHP = Rhineland-Palatine, SAAR = Saarland, SACH = Saxony, ST = Saxony-Anhalt, SH = Schleswig-Holstein, TH = Thuringia. *Source*: Data from Destatis (2008a)

Fig. 2.2 Gross and net migration flows between East and West Germany 1991–2006. *Source*: Data from Destatis (2008a)



2.5 Dynamic Panel Data Estimators in a VAR Framework

The Panel VAR (PVAR) technique combines the traditional VAR approach treating all variables of the system as endogenous with estimation techniques for panel data and was first employed by Holtz-Eakin et al. (1988). While the use of VAR models in time series analysis is a common standard, the use in a panel data context is less

Table 2.2 Im–Pesaran–Shin (2003) panel unit root test for variables

Specification	IPS test for $N \times (N-1)$, $T = (240, 16)$ H_0: All panels contain unit roots		
	W[t-bar]	p-value	Lags
$nm_{ij,t}$	−16.75	(0.00)	0.36
$\widetilde{ur}_{ij,t}$	−17.69	(0.00)	0.64
$\widetilde{wr}_{ij,t}$	−96.09	(0.00)	0.55
$\Delta\widetilde{ylr}_{ij,t}$	−67.42	(0.00)	0.34
$\tilde{q}_{ij,t}$	−15.59	(0.00)	0.59
$\widetilde{hc}_{ij,t}$	−21.56	(0.00)	0.33

Note: Including a constant term; optimal (average) lag length selection according to the AIC

common. However, a recent comparison of different PVAR estimators together with a Monte Carlo simulation experiments for standard small T, large N data settings is given by Binder et al. (2005). As Mäki-Arvela (2003) argues, the unrestricted VAR methodology is ideally suited for an examination of interrelated time series variables and their dynamics in a labor market setting, where a particular focus is to explore the strengths of different adjustment mechanisms in response to economic shocks. Throughout the analysis we restrict our estimation approach to a first-order PVAR(1) written in matrix form as:[10]

$$z_{i,t} = \Gamma_0 + \Gamma_1 z_{i,t-1} + e_{i,t} \tag{2.9}$$

where $z_{i,t}$ is an $m \times 1$ vector. In our case, $z_{i,t} = [nm_{ij,t}, \widetilde{wr}_{ij,t}, \widetilde{ur}_{ij,t}, \Delta\widetilde{ylr}_{ij,t}, \tilde{q}_{ij,t}, \widetilde{hc}_{ij,t}]$, Γ_1 is an $m \times m$ matrix of slope coefficients, $e_{i,t}$ is an $m \times 1$ vector of the composed error term as discussed above, including unobserved individual effects and a remainder component. The PVAR(1) model is thus a straightforward generalization of a univariate dynamic panel data model.

There are numerous contributions in the recent literature for a dynamic single equation model of the above type, which especially deal with the problem introduced by the inclusion of the lagged dependent variable on the right hand side of the estimation equation and its built-in correlation with the combined error term. Arellano and Bond (1991), for instance, propose an GMM estimator in first differences, which employs valid instruments for the lagged endogenous variable of the form:

$$E(y_{i,t-\rho}\Delta u_{i,t}) = 0 \quad \text{for all } \rho = 2, \ldots, t-1. \tag{2.10}$$

Equation (2.10) is also called the 'standard moment condition' and is widely used in empirical estimation. The resulting instrument matrix for past values of the endogenous variable can then be written as:

[10] As Binder et al. (2005) note, higher-order models can be treated in conceptually the same manner as the first-order representation. For ease of presentation, we denote the cross section dimension by i rather than ij.

$$Z_i^{\Delta,(y)} = \begin{pmatrix} y_{i0} & 0 & \cdots & \cdots & 0 & \cdots & 0 \\ 0 & y_{i0} & y_{i1} & 0 & 0 & \cdots & 0 \\ 0 & \cdots & \cdots & \vdots & \vdots & \cdots & 0 \\ 0 & \cdots & 0 & 0 & y_{i0} & \cdots & y_{iT-2} \end{pmatrix} \tag{2.11}$$

and analogously for the set of strictly exogenous explanatory variables (X_{it-1}):

$$Z_i^{\Delta,(x)} = \begin{pmatrix} x'_{i0} & \cdots & x'_{iT-1} & 0 & \cdots & \cdots & 0 & \cdots & 0 \\ 0 & \cdots & 0 & x'_{i0} & \cdots & x'_{iT} & 0 & \cdots & 0 \\ 0 & \cdots & & & \cdots & 0 & \cdots & & 0 \\ 0 & \cdots & \cdots & & \cdots & 0 & x'_{i0} & \cdots & x'_{i,T-1} \end{pmatrix} \tag{2.12}$$

and the full instrumental variable set for the first-difference (FD) transformed model (Z_i^{Δ}) is given by

$$Z_i^{\Delta} = (Z_i^{\Delta,(y)}, Z_i^{\Delta,(X)}). \tag{2.13}$$

One general drawback of dynamic model estimators in first differences is their rather weak empirical performance. As Bond et al. (2001) argue, IV and Generalized Method of Moments (GMM) estimators in first differences can behave poorly, since lagged levels of the time series provide only 'weak instruments' for subsequent first-differences. In response to this critique, a second generation DPD models has been developed, which also makes use of appropriate orthogonality conditions for the equation in levels (see, e.g., Blundell and Bond 1998) as:

$$E(\Delta y_{i,t-1} u_{i,t}) = 0 \quad \text{for } t = 3, \ldots, T. \tag{2.14}$$

Rather than using lagged levels of variables for equations in first difference as in the case of FD-estimators, we get an orthogonality condition for the model in level that uses instruments in first differences.

Equation (2.14) is also called the 'stationarity moment condition'. Blundell and Bond (1998) propose a GMM estimator that uses jointly both the standard and stationarity moment conditions. This latter approach is typically known as 'system' GMM (SYS-GMM) combining 'level' and 'difference' GMM. Though labeled system GMM, this estimator treats the data system as a single-equation problem since the same linear functional relationship is believed to apply in both the transformed and untransformed variables as

$$\begin{pmatrix} \Delta y \\ y \end{pmatrix} = \alpha \begin{pmatrix} \Delta y_{-1} \\ y_{-1} \end{pmatrix} + \beta \begin{pmatrix} \Delta X_{-1} \\ X_{-1} \end{pmatrix} + \begin{pmatrix} \Delta u \\ u \end{pmatrix} \tag{2.15}$$

and the overall instrument set in the case of system GMM is $Z_i = (Z_i^{\Delta}, Z_i^{L})$, where the latter is the instrument set for the equation in levels based on valid orthogonality conditions for $y_{i,t-1}$ and $X_{i,t-1}$.

For the empirical estimation of our PVAR model, we employ multiple-equation GMM (as, e.g., outlined in Hayashi 2000), which basically involves stacking our migration and labor market model in the typical system way (3SLS or SUR) and apply IV estimation using the SYS-GMM estimation strategy. The resulting IV set Z_i^S for a system of m equations (with $m = 1, \ldots, M$) is a combination of the individual equations' IV sets, where we allow the instruments to differ among the equations of the system as

$$Z_i^S = \begin{bmatrix} Z_{i1} & \cdots & 0 \\ \vdots & \ddots & \vdots \\ 0 & \cdots & Z_{iM} \end{bmatrix}. \tag{2.16}$$

Stacking the equations for multiple-equation GMM estimation may lead to further efficiency gains if the residuals of the M equations are correlated. We therefore apply a two-step approach which explicitly accounts for cross-equation residual correlation. The weighting matrix V^S in two-step efficient GMM estimation is defined as

$$V^S = N^{-1} \sum_{i=1}^{N} Z_i^{S\prime} \hat{e}_i \hat{e}_i' Z_i^S \tag{2.17}$$

and the vector of first step error terms $\hat{e}_i = (\hat{e}_{i1}, \ldots, \hat{e}_{iM})'$ is derived from a consistent (equation by equation) 2SLS estimation. The system GMM estimator in the context of the PVAR(1) can then be written as:

$$\hat{\Phi}_{GMM} = \left(S_{ZX}' (V^S)^{-1} S_{ZX} \right)^{-1} S_{ZX}' (V^S)^{-1} S_{Zy}, \tag{2.18}$$

with

$$S_{ZX} = \begin{bmatrix} \frac{1}{N} \sum_{i=1}^{N} z_{i1}' x_{i1} & & \\ & \ddots & \\ & & \frac{1}{N} \sum_{i=1}^{N} z_{iM}' x_{iM} \end{bmatrix} \quad \text{and}$$
$$S_{Zy} = \begin{bmatrix} \frac{1}{N} \sum_{i=1}^{N} Z_{i1}' y_{i1} \\ \vdots \\ \frac{1}{N} \sum_{i=1}^{N} Z_{iM}' y_{iM} \end{bmatrix}. \tag{2.19}$$

2.6 Empirical Results

In this section we present the empirical results of the PVAR(1) model.[11] We first look at the estimation output and post estimation tests and then analyze the dynamic adjustment processes in terms of impulse response functions. One major concern in our modelling approach is to carefully check for the consistency and efficiency of the chosen estimation approach. Since the system GMM approach relies on IV estimation, we basically guide instrument selection based on the Sargan (1958)/Hansen (1982) overidentification test. Especially in a multiple equation context, appropriate IV selection is of vital importance since the full IV candidate set may become

[11] At this point, we focus on the PVAR(1) case since longer time lags are hardly applicable given the rather short overall sample period.

large. One has to note that the power of the Hansen J-statistic shrinks with increasing instrument number (see, e.g., Bowsher 2002, and Roodman 2009). The standard Sargan statistic is however robust to this problem. We thus use a procedure to reduce the number of orthogonality conditions employed for estimation, both by using 'collapsed' IV sets as well as by sorting out correlated variables with the help of the C-statistic (or 'Diff-in-Sargan/Hansen's J') as numerical difference of two overidentification tests isolating IVs under suspicion (see Eichenbaum et al. 1988, for details). Additionally, we check the likely efficiency gains of the system SYS-GMM estimation approach in terms of testing for cross-equation correlations for the first step residuals.

The estimation results for the PVAR(1) model based on the efficient two-step system SYS-GMM approach are reported in Table 2.3.[12] The estimation results for the migration equation show that the core labor market variables (both real wage and unemployment differentials as well as labor productivity growth) are statistically significant and of expected signs. Only the participation rate is statistically

Table 2.3 Estimation results—Panel VAR with lag(1) for $[nm_{ij,t}, \widetilde{wr}_{ij,t}, \widetilde{ur}_{ij,t}, \Delta\widetilde{ylr}_{ij,t}, \tilde{q}_{ij,t}, \widetilde{hc}_{ij,t}]$

Dep. var.	r.h.s. var.	Coef.	Corr. S.E.	t-stat.	p-value
$nm_{ij,t}$	$nm_{ij,t-1}$	0.43^{***}	0.051	8.41	(0.00)
$nm_{ij,t}$	$\widetilde{wr}_{ij,t-1}$	0.49^{***}	0.144	3.41	(0.00)
$nm_{ij,t}$	$\widetilde{ur}_{ij,t-1}$	-0.12^{**}	0.050	−2.46	(0.01)
$nm_{ij,t}$	$\Delta\widetilde{ylr}_{ij,t-1}$	0.66^{***}	0.073	9.06	(0.00)
$nm_{ij,t}$	$\tilde{q}_{ij,t-1}$	0.02	0.277	0.07	(0.94)
$nm_{ij,t}$	$\widetilde{hc}_{ij,t-1}$	-0.02^{*}	0.012	−1.78	(0.07)
$\widetilde{wr}_{ij,t}$	$nm_{ij,t-1}$	-0.02^{***}	0.003	−4.89	(0.00)
$\widetilde{wr}_{ij,t}$	$\widetilde{wr}_{ij,t-1}$	0.46^{***}	0.028	16.32	(0.00)
$\widetilde{wr}_{ij,t}$	$\widetilde{ur}_{ij,t-1}$	-0.10^{***}	0.030	−3.35	(0.00)
$\widetilde{wr}_{ij,t}$	$\Delta\widetilde{ylr}_{ij,t-1}$	0.12^{***}	0.015	7.70	(0.00)
$\widetilde{wr}_{ij,t}$	$\tilde{q}_{ij,t-1}$	0.71^{***}	0.105	6.77	(0.00)
$\widetilde{wr}_{ij,t}$	$\widetilde{hc}_{ij,t-1}$	−0.001	0.001	−1.37	(0.17)
$\widetilde{ur}_{ij,t}$	$nm_{ij,t-1}$	0.06	0.038	1.54	(0.12)
$\widetilde{ur}_{ij,t}$	$\widetilde{wr}_{ij,t-1}$	-0.29^{***}	0.063	−4.68	(0.00)
$\widetilde{ur}_{ij,t}$	$\widetilde{ur}_{ij,t-1}$	0.067^{***}	0.055	12.07	(0.00)
$\widetilde{ur}_{ij,t}$	$\Delta\widetilde{ylr}_{ij,t-1}$	-0.39^{***}	0.042	−9.42	(0.00)
$\widetilde{ur}_{ij,t}$	$\tilde{q}_{ij,t-1}$	-0.99^{***}	0.244	4.06	(0.00)
$\widetilde{ur}_{ij,t}$	$\widetilde{hc}_{ij,t-1}$	0.02^{***}	0.005	4.10	(0.00)

(*continued on the next page*)

[12] Details about the IV downward testing approach with an example for the migration equation are given in Appendix A.

Table 2.3 (Continued)

Dep. var.	r.h.s. var.	Coef.	Corr. S.E.	t-stat.	p-value
$\Delta\widetilde{ylr}_{ij,t}$	$nm_{ij,t-1}$	−0.03	0.017	−1.52	(0.13)
$\Delta\widetilde{ylr}_{ij,t}$	$\widetilde{wr}_{ij,t-1}$	−0.23***	0.051	−4.51	(0.00)
$\Delta\widetilde{ylr}_{ij,t}$	$\widetilde{ur}_{ij,t-1}$	0.09***	0.023	3.90	(0.00)
$\Delta\widetilde{ylr}_{ij,t}$	$\Delta\widetilde{ylr}_{ij,t-1}$	0.55***	0.024	22.61	(0.00)
$\Delta\widetilde{ylr}_{ij,t}$	$\tilde{q}_{ij,t-1}$	0.46***	0.124	3.71	(0.00)
$\Delta\widetilde{ylr}_{ij,t}$	$\widetilde{hc}_{ij,t-1}$	0.17***	0.026	6.41	(0.00)
$\tilde{q}_{ij,t}$	$nm_{ij,t-1}$	0.01***	0.001	4.03	(0.00)
$\tilde{q}_{ij,t}$	$\widetilde{wr}_{ij,t-1}$	0.08***	0.006	12.70	(0.00)
$\tilde{q}_{ij,t}$	$\widetilde{ur}_{ij,t-1}$	−0.01**	0.003	−2.52	(0.01)
$\tilde{q}_{ij,t}$	$\Delta\widetilde{ylr}_{ij,t-1}$	0.09***	0.004	24.70	(0.00)
$\tilde{q}_{ij,t}$	$\tilde{q}_{ij,t-1}$	0.81***	0.014	54.67	(0.00)
$\tilde{q}_{ij,t}$	$\widetilde{hc}_{ij,t-1}$	−0.01***	(0.001)	−4.56	(0.00)
$\widetilde{hc}_{ij,t}$	$nm_{ij,t-1}$	0.07**	0.031	2.18	(0.02)
$\widetilde{hc}_{ij,t}$	$\widetilde{wr}_{ij,t-1}$	0.31***	0.140	2.23	(0.03)
$\widetilde{hc}_{ij,t}$	$\widetilde{ur}_{ij,t-1}$	−0.15***	0.033	−4.36	(0.00)
$\widetilde{hc}_{ij,t}$	$\Delta\widetilde{ylr}_{ij,t-1}$	0.24***	0.071	3.43	(0.00)
$\widetilde{hc}_{ij,t}$	$\tilde{q}_{ij,t-1}$	−0.07	0.306	−0.24	(0.81)
$\widetilde{hc}_{ij,t}$	$\widetilde{hc}_{ij,t-1}$	0.55***	0.057	9.70	(0.00)
No. of obs. per eq.			3120		
No. of system obs.			18720		
No. of instruments			222		
F-test (joint significance)			608.6		
			(0.00)		
Sargan statistic			179.1		
			(0.61)		
Hausman $\lvert m \rvert$-stat.			2.45		
			(0.99)		
$\chi^2_{CE}(15)$			33.47		
			(0.00)		

Note: Standard errors are computed based on Windmeijer's (2005) finite-sample correction. χ^2_{CE}: Test for cross-equation correlation of the system's 1.step residuals as outlined in Dufour and Khalaf (2002)

*Denote statistical significance at the 10% level **Denote statistical significance at the 5% level
***Denote statistical significance at the 1% level

insignificant. The negative coefficient for human capital may be explained by the equilibrating effect of regional differences in human capital endowment on migration flows after controlling for the other explanatory labor market factors. However, this latter partial equilibrium view may not reflect the full direct and indirect effect of regional human capital differences on migratory movements, which has to be analyzed through impulse–response functions (e.g., in order to capture the likely link between human capital and productivity growth, which in turn may translate into a positive migration response due to a shock in regional human capital differences). Finally, we include a dummy variable for Lower Saxony (D_{NIE}), which turns out to be negative and statistically highly significant.

If we turn to the postestimation tests, Table 2.3 reports the robust Sargan statistic for our 222 chosen instruments (out of a maximum of 2382 in the full 'uncollapsed' IV case). Our proposed IV set passes the test statistic for reasonable confidence levels. Moreover, we compute a Breusch–Pagan LM test for the significance of cross-effects in the first step residuals (χ^2_{CE}) as suggested in Dufour and Khalaf (2002) in order to check for the likely efficiency gains in applying a full information approach. The Breusch–Pagan type test clearly rejects the null hypothesis of independence among the residuals of our 6-equation system. Finally, in order to compare the appropriateness of our chosen efficient two-step approach relative to a limited information 2SLS benchmark, we employ the Hausman (1978) m-statistics.[13] The results do not reject the null of consistency and efficiency of our two-step approach compared to the one-step specification.

If we take a look at the estimated coefficients in the remaining equations in the PVAR(1) model, Table 2.3 shows that lagged migration has a significantly negative direct effect on the wage rate, while the impact on the participation rate and the human capital index is positive. These results already hint at the important role of instantaneous causality among the variables and support our theoretical expectations that migration has an equilibrating effect on regional labor markets in line with the neoclassical model. That is, an increased level of net in-migration in region i lowers the regional wage rate differential (the wage in region i decreases relative to j) and thus works towards a cross-regional wage equalization as outlined above. Our empirical results also indicate the existence of a wage curve a la Blanchflower and Oswald (1994, 2005) since, in the wage equation, the unemployment rate has a negative coefficient sign.

Labor productivity growth has a positive impact on the wage rate, while in the equation for labor productivity growth, the wage rate itself has a negative effect. In the equation for the labor participation rate, the wage rate is estimated to have a positive effect, while unemployment is negatively correlated with the participation rate. The equation for human capital mainly mirrors earlier micro results finding a positive impact of wage rates and labor productivity on regional human capital

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[13] By construction, if the variance of the limited information approach is larger than its full information counterpart, the test statistic will be negative. Though the original test is typically not defined for negative values, here we follow Schreiber (2007) and take the absolute value of the m-statistics as indicator.

endowments, while higher unemployment rates are negatively correlated with the regional human capital endowment. Finally, net in-migration is estimated to have a positive effect on the relative regional distribution of human capital. Whether this latter effect may hint at the possible role of regional ‘brain drain’ effects will be analyzed through the help of impulse–response functions.

In order to assess the two-way effects among migration and labor market variables, we compute impulse–response functions of the PVAR. The latter tool describes the reaction of one variable to innovations in another variable of the system, while holding all other shocks equal to zero (for details see Lütkepohl 2005). Figures 2.3 and 2.4 plot impulse–response functions together with 5 percent errors bands generated through Monte Carlo simulations with 500 repetitions.[14] Additionally, Table 2.4 reports variance decompositions derived from the orthogonalized impulse–response coefficient matrices. The variance decompositions display the proportion of movements in the dependent variables that are due to their own shocks versus shocks to the other variables, which is done by determining how much of an s-step ahead MSE forecast error variance for each variable is explained by innovations to each explanatory variable (we report s until 20).

Figure 2.3 shows the responses of migration to a one standard deviation shock in the remaining variables of the PVAR (rescaled in terms of shocks of one standard deviation). As the figure shows, the shock to unemployment changes is negative with most of the migration response being absorbed after three to four years (similar results for West Germany are obtained in Möller 1995). The response to a shock in the regional wage rate differential has the expected positive dynamics. The migration responses to labor productivity and human capital shocks turn out to be positive and show a higher degree of persistence. Especially for human capital, the overall effect in the system context is thus different from the partial equilibrium view. Though the direct effect of regional human capital differences on net in-migration gave some indication for an equilibrating effect after controlling for key labor market factors, the overall effect obtained from the impulse–response functions shows that a relatively better skill composition in region i acts as a pull factor for additional net in-migration reflecting disequilibrating or agglomeration forces associated with scale effects (e.g. in the educational system). The link from human capital to enhanced in-migration is especially expected to work through the productivity growth channel of human capital, which has been tested highly significant in the PVAR(1) estimation results. The negative migration response to a positive shock in the labor participation rate may hint at the role of regional labor market tightness, which reduces net in-migration.

[14] A full graphical presentation of the system’s impulse–response functions is given in Appendix B. For the orthogonalized impulse–response functions we choose the following causal ordering $[\widetilde{hc}_{ij,t} \to \tilde{q}_{ij,t} \to \widetilde{ylr}_{ij,t} \to \widetilde{wr}_{ij,t} \to \widetilde{ur}_{ij,t} \to \widetilde{nm}_{ij,t}]$, which is based on the assumption that migration and the core labor market variables are more endogenous compared productivity growth, labor participation (due to its demographic component) and human capital endowment. Results for reversed ordering can be obtained from the authors upon request. They are much in line with our original choice of ordering.

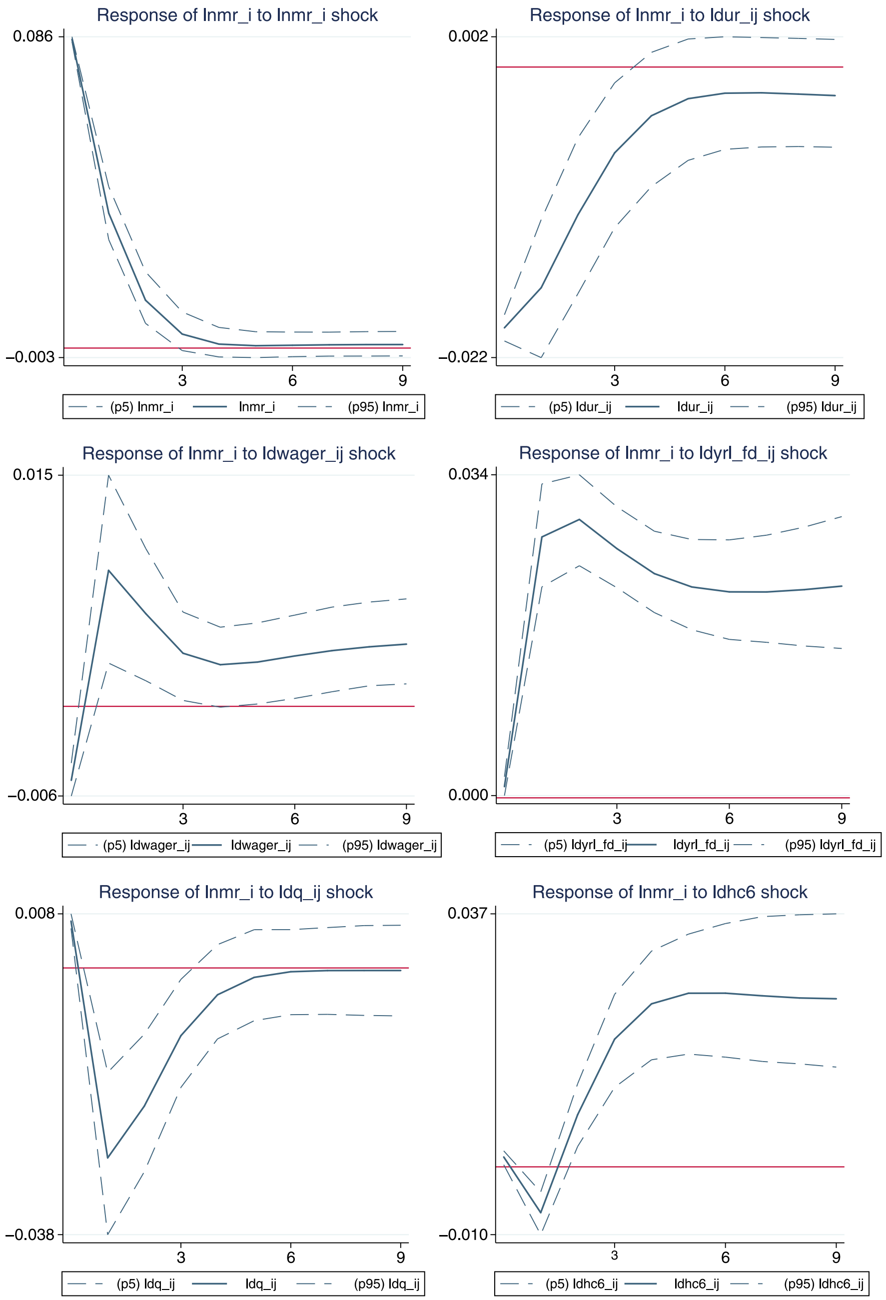

Fig. 2.3 Migration responses to shocks of one standard deviation in the variables from the PVAR(1). *Note*: Confidence intervals based on MC-simulations with 500 reps. With $nm_{ij,t}$ = lnmr_i, $\widetilde{ur}_{ij,t}$ = ldur_ij, $\widetilde{wr}_{ij,t}$ = ldwager_ij, $\widetilde{ylr}_{ij,t}$ = ldyrl_fd_ij, $\tilde{q}_{ij,t}$ = ldq_ij, $\widetilde{hc}_{ij,t}$ = ldhc6_ij

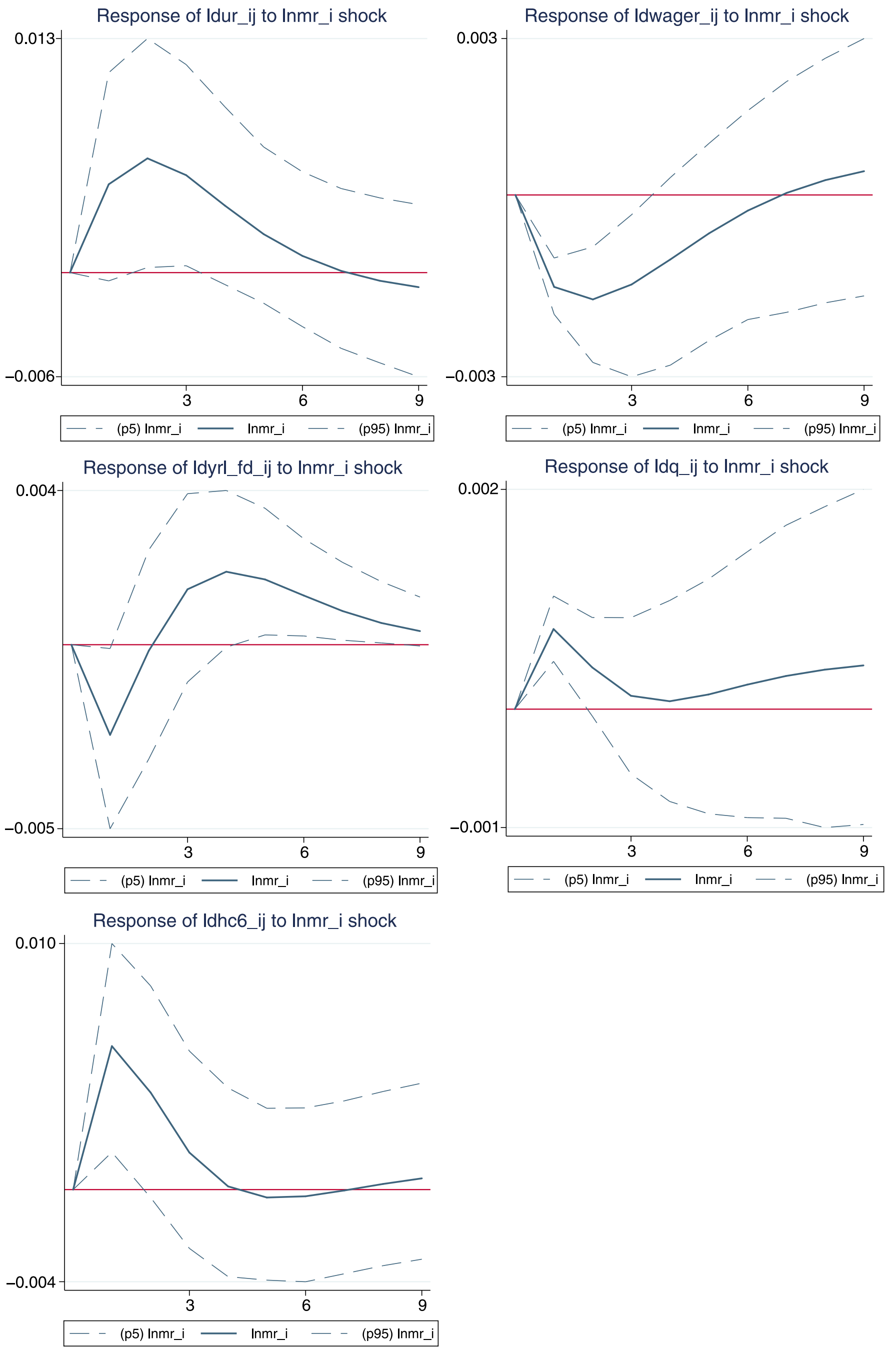

Fig. 2.4 Variable responses in the PVAR(1) to a shock of one standard deviation in the migration rate. *Note*: Confidence intervals based on MC-simulations with 500 reps. With $nm_{ij,t}$ = lnmr_i, $\widetilde{ur}_{ij,t}$ = ldur_ij, $\widetilde{wr}_{ij,t}$ = ldwager_ij, $\widetilde{ylr}_{ij,t}$ = ldyrl_fd_ij, $\tilde{q}_{ij,t}$ = ldq_ij, $\widetilde{hc}_{ij,t}$ = ldhc6_ij

Table 2.4 Variance decomposition with percent variation in row variable explained by column variable

	s	$nm_{ij,t}$	$\widetilde{ur}_{ij,t}$	$\widetilde{wr}_{ij,t}$	$\Delta\widetilde{ylr}_{ij,t}$	$\tilde{q}_{ij,t}$	$\widetilde{hc}_{ij,t}$
$nm_{ij,t}$	5	0.590	0.056	0.010	0.188	0.084	0.069
$\widetilde{ur}_{ij,t}$	5	0.008	0.548	0.009	0.191	0.201	0.041
$\widetilde{wr}_{ij,t}$	5	0.004	0.057	0.324	0.228	0.334	0.051
$\Delta\widetilde{ylr}_{ij,t}$	5	0.003	0.036	0.009	0.413	0.123	0.415
$\tilde{q}_{ij,t}$	5	0.002	0.008	0.045	0.508	0.311	0.126
$\widetilde{hc}_{ij,t}$	5	0.002	0.021	0.004	0.047	0.039	0.886
$nm_{ij,t}$	10	0.428	0.042	0.010	0.252	0.061	0.205
$\widetilde{ur}_{ij,t}$	10	0.005	0.318	0.013	0.331	0.114	0.217
$\widetilde{wr}_{ij,t}$	10	0.002	0.034	0.173	0.380	0.168	0.241
$\Delta\widetilde{ylr}_{ij,t}$	10	0.003	0.035	0.009	0.391	0.116	0.444
$\tilde{q}_{ij,t}$	10	0.001	0.004	0.027	0.506	0.096	0.364
$\widetilde{hc}_{ij,t}$	10	0.002	0.021	0.006	0.118	0.033	0.818
$nm_{ij,t}$	20	0.256	0.027	0.012	0.332	0.036	0.334
$\widetilde{ur}_{ij,t}$	20	0.002	0.131	0.014	0.408	0.046	0.396
$\widetilde{wr}_{ij,t}$	20	0.001	0.015	0.072	0.431	0.061	0.418
$\Delta\widetilde{ylr}_{ij,t}$	20	0.003	0.034	0.009	0.390	0.115	0.446
$\tilde{q}_{ij,t}$	20	0.001	0.004	0.019	0.472	0.029	0.473
$\widetilde{hc}_{ij,t}$	20	0.001	0.015	0.009	0.232	0.022	0.718

Note: Based on the orthogonalized impulse–responses, details see text

This general picture is also supported by plotting the forecast error variance decompositions in Table 2.4. In the short run, a shock in the unemployment rate has the biggest effect on net in-migration (with a maximum after 3 periods). In the long run, most of the error variance in net in-migration is accounted for by shocks in labor productivity growth and human capital. If we look at the impulse–response functions of the remaining variables of the system subject to a one standard deviation shock in net in-migration, we get a similar picture: For the unemployment rates and real wages Fig. 2.4 shows the equilibrating effect of a positive shock in the in-migration rate: Regional differences in the unemployment rate increase in response to an inflow of migrants, while regional wage rate differentials are reduced (though smaller in magnitude). Responses of labor productivity and labor participation with respect to migration are positive but rather marginal, while the impact on human capital shows indeed some indication for regional 'brain drain' effects given that net out-migration negatively affects the regional skill composition (and vice versa).

The impulse responses and the computation of forecast error variance decompositions give the general impression that most adjustment processes in the PVAR system fade out rapidly. Only migration responses to shocks in labor productivity growth and human capital endowment indicate persistent effects. Moreover, beside those effects involving migration either as source or destination of shocks, the PVAR system gives further helpful insights for a better understanding of regional labor market and macroeconomic dynamics in Germany. A full graphical description of the impulse–response functions is given in Fig. 2.8. If we look, for example, at the response of real wages and human capital endowment to a shock in regional unemployment, we see the following reaction. In both cases, the impulse–response functions show a significantly negative adjustment process, which only fades out gradually. Likewise a shock in the unemployment rate leads to a deterioration of the regional human capital endowment, which supports the view of regional 'brain drain' effects as a reaction to regional labor market differences operating through the above identified migration channel.

Given the overall satisfactory model reactions of our PVAR(1), we will finally apply the model to the challenging question in how far our small scale system is able to track the distinct East–West net out-migration trend since re-unification and to explain the East German "empirical puzzle".

2.7 East–West Migration: Still an "Empirical Puzzle"?

We have already seen from the stylized facts that East–West net out-migration made up a large part of overall German internal migration flows. Moreover, we did not observe a steady stream of migratory movements but rather two distinct waves. The first one directly started after opening up the intra-German border and thereafter declined until 1997. The late 1990s then witnessed a second wave of East–West net out-migration with a distinct peak in 2001. It thus may be a challenging task to carefully check, whether the specific path of East–West migration can be explained within the above-specified neoclassical migration model embedded in the PVAR(1). We are thereby especially interested in answering the following question: Can we explain these distinct ups and downs in East–West net migration on grounds of regional disparities in labor market variables? Or are they due to other unobserved and possibly non-economic factors, which are present in the two macro regions?

The question of East–West migration is also of special interest since earlier findings in Alecke and Untiedt (2000) gave rise to such a German "empirical puzzle" in line with similar evidence found for the Italian case, where macroeconomic Harris–Todaro inspired models were only found helpful in predicting changes in migration trends, but not in their absolute levels. Both for German East–West and Italian South–North migration flows, a high degree of "immobility" was found to coexist with large regional labor market disparities.[15] To find an appropriate answer to this puzzle of insufficient migration to equilibrate regional labor market disparities is of

[15] For a discussion of the Italian case see, e.g., Fachin (2007) or Etzo (2007).

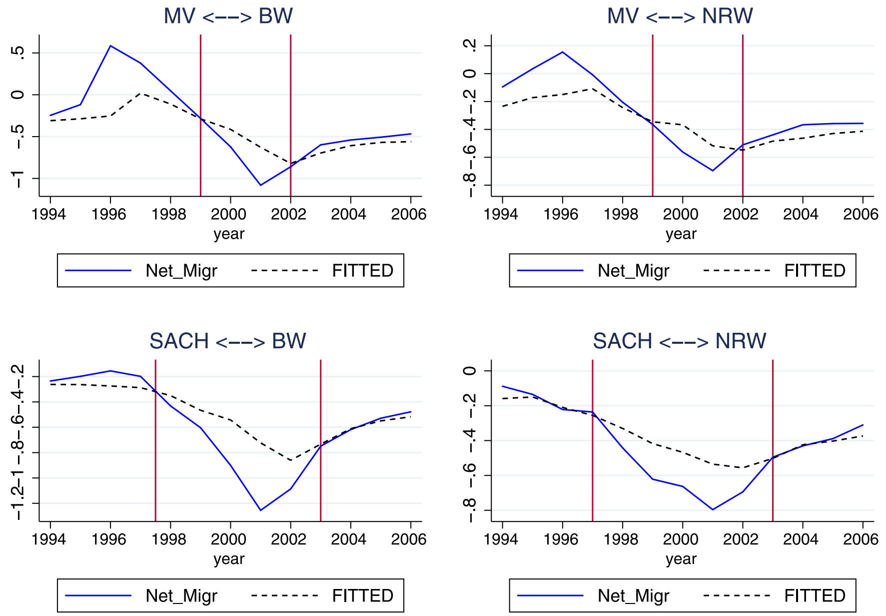

Fig. 2.5 Actual and fitted net migration for selected East–West state pairs. *Note*: BW = Baden-Württemberg, MV = Mecklenburg-Vorpommern, NRW = North Rhine-Westphalia, SACH = Saxony

special importance for determining the role of migratory movements in the process of regional economic development and income convergence. A first check for the empirical performance of our PVAR(1) model in the light of East–West migration is thus to compare the actual and (in-sample) predicted net migration flows for the involved state pairs.

In Fig. 2.5, we report the results for two selected state pairs including the East German regions Mecklenburg-Vorpommern and Saxony and their interaction with the two Western counterparts Baden-Württemberg and North Rhine-Westphalia for illustration purposes.[16] As the results in Fig. 2.5 show, on average there is a rather high concordance of actual and fitted values over time for most bilateral pairs indicating that the estimated elasticities for the total German sample in conjunction with the temporal variation in the explanatory variables are able to explain the distinct trends in the East–West migration since 1994. However, though we see that the model is generally well equipped to predict changes in migratory movements for a variety of state pairs we observe a gap in the level of actual and predicted net migration flows over time, which may require a closer examination beyond the labor market signals.

[16]Detailed graphical plots for all East–West pairs are given in Fig. 2.9 in Appendix B.

In the exemplary case of net flows from Mecklenburg-Vorpommern and Saxony relative to Baden-Württemberg and North Rhine-Westphalia, we get the following picture. In the first part of the in-sample period until 1997, we gather from Fig. 2.5 that the structural labor market model over fits observed net migration, that is, actual net outflows out of the two East German states are much smaller than their predicted values. This result is in line with earlier evidence given in Alecke and Untiedt (2000) as well as Fachin (2007) for the Italian case. However, during the second wave of East–West migration with its peak around 2001 this relationship is reversed resulting in higher actual net outflows than predicted values based on the included structural labor market parameters. Towards the sample end actual and fitted values are again more closely in line, indicating that labor market signals now properly translate into migratory flows between East and West Germany.

In solving this implied "empirical puzzle" one prominently advocated line of argumentation in the field of regional science speaks in favor of fixed regional amenities to explain persistent labor market differences even in the long-term equilibrium. Thereby, regional amenities are typically defined as a proxy variable for (unobserved) specific climatic, ecological or social conditions in a certain region. According to the amenity approach, regional differences in labor market signals then only exhibit an effect on migration after a critical threshold has been passed. Since, in empirical terms, it is often hard to operationalize amenity relevant factors, Greenwood et al. (1991) propose to test the latter effect by the inclusion of (macro-)regional dummy variables in the empirical model. For the long run net migration equation, amenity-rich regions then should have dummy coefficients greater than zero (and vice versa), indicating that amenity-rich regions exhibit higher than average in-migration rates as we would expected after controlling for regional labor market and macroeconomic differences.

To test the above hypothesis, we thus augment the PVAR(1) by a dummy variable (for each equation) capturing inter-regional migration flows for the East German macro region. We also specify an alternative model specification with a similar dummy variable for East–West border regions. In order to analyze the time evolution of these dummies, we use a recursive estimation strategy in the following way:

$$Dummy_{[East;Border]} = \begin{cases} 1 & \text{for 1991 until } s\text{, with } s = 1997, \ldots, 2006, \\ 0 & \text{otherwise.} \end{cases} \tag{2.20}$$

The results generally show that the inclusion of the dummy variables does not affect the coefficients of the structural variables in the system. The results for the migration equation also indicate that the East dummy is insignificant for the whole sample with $s = 2006$. However, in line with Alecke and Untiedt (2000), the dummy variable for $s = 1997$ shows a positive and statistically significant coefficient sign. Similar results are found for the border dummy. For the recursive estimation experiment, we plot the time evolution of two dummy coefficients together with their respective t-values and the 10 percent critical t-value. For the East dummy in Fig. 2.6, we see that the coefficient is statistically significant and positive only up to 1997,

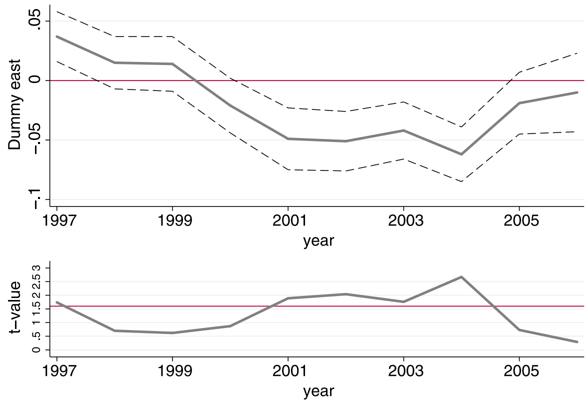

Fig. 2.6 Time evolution of the East German dummy in the augmented PVAR(1)

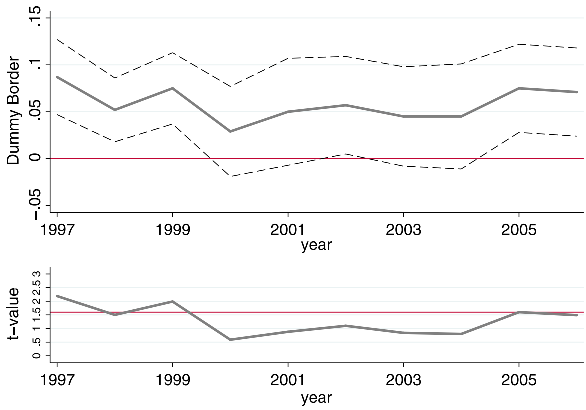

Fig. 2.7 Time evolution of the East–West border dummy in the augmented PVAR(1)

while it becomes insignificant or even turns significantly negative for subsequent periods. The latter finding coincides with the peak of the second huge wave of East–West net out-migration around 2001. The coefficient of the border dummy remains positive for the whole sample period but is found to be statistically significant only between 1997 and 1999 and again in 2005 (see Fig. 2.7).

When interpreting these results, it does not seem reasonable to take a positive dummy variable in favor of any kind of climatic or similar ecological regional fixed amenities for the East German states that keep people living there (which actually may be true for the case of Hawaii but not for Bitterfeld). A further substantial critique to the amenities interpretation of the dummy variable approach is that the latter can only be interpreted as amenities under the premise that the influence of other latent variables on regional net migration is of negligible order. However, this is more than doubtful with respect to the East German states if we, for example, consider the determinants of individual migration decisions (as worked out in the field of microeconomic migration theories) including the age structure of the work force potential, the relative wage structure, network effects, or the option value of waiting. Moreover, the analysis has only implicitly (via the labor participation rate) tackled the issue of particular high commuter flows between East and West, which may be seen as a substitute to the migration decision and give a reasonable explanation for the positive dummy variable coefficient of the Eastern border regions.

Finally and maybe most important from an aggregate East German perspective, politically induced distortions to the East German labor market and general economy may be seen as an impediment to sufficient high migration rates as balancing factor for regional labor market disparities until the mid-1990s. The latter comprises for instance a politically driven fast wage adjustment in the East (see Burda and Hunt 2001, for details on this point), as well as massive West–East financial transfers (see e.g. Bradley et al. 2006), which kept people away from leaving the Eastern states. Only recently, these transfers have been reduced in volume and now gradually fade out (e.g., the Solidarity Pact II), which in turn may explain the second wave of East German net out-migration and the estimated negative dummy variable coefficient for that period. In this interpretation the negative dummy variable hints at "repressed" migration potential in East Germany as for that period, which only cancels out in the end of the sample period along with a gradual fading out of labor market and macroeconomic distortions. A similar line of argumentation can be found for a downward sizing in expectations about the speed of convergence in East–West standards of living.

Also for the remaining equations of the PVAR(1), the inclusion of dummy variables gives some interesting results with respect to East–West labor market and macroeconomic disparities. With respect to the unemployment rate, the East dummy shows the expected negative level effect between the Eastern and Western regions even after controlling for key labor market factors and also seems to worsen over time given the strong increase in the coefficient of the dummy variable coefficient. For East German border regions, this negative effect seems to be less present. Another key fact is that growth in labor productivity does not show significant differences for the two macro-regions during the sample period 1994–2006 (after controlling for labor market differences).

This result mirrors empirical results reported in Smolny and Stiegler (2004), finding that productivity adjustment in the East German states was fast in the early years after 1991, but also that the equilibrium gap to the Western average is large (the authors calculate a gap of about 35 percent, which explains the significant reduction in the convergence speed of the East German states starting from the second half of the 1990s). Similar results were also obtained for the wage rate, for which we get insignificant dummy variable coefficients in the PVAR(1). Finally, for both border regions and East Germany as a whole, the human capital equation shows that the region has subsequently lost its initial advantage in human capital endowment. This latter trend is typically associated with the above identified 'brain drain' effect for East Germany (see also Schneider 2005). Summing up, these results call for further in-depths studies on the long-run structural differences in key labor market and economic indicators for the two East–West macro-regions almost twenty years after re-unification.

2.8 Conclusion

Throughout this chapter we have analyzed the linkages between regional disparities in labor market variables and interregional migration flows among German states since re-unification. Building upon recent methodological advances in the analysis of (dynamic) panel data models, we have specified a VAR model for panel data using efficient GMM estimation as proposed by Blundell and Bond (1998). One advantage of our chosen approach is that it allows us to appropriately handle the issues of endogeneity, simultaneity and multi-way feedback relationships among variables in the system. By the computation of impulse–response functions, we are able to check for the full dynamic properties of our estimated Panel VAR system and to evaluate the responses of migratory movements to different labor market shocks. Turning to the empirical results, we identify a clear role of regional disparities in the real wage and unemployment rate as major driving forces of internal migration in Germany. We also find that regional differences in labor productivity growth induce net migration flows, while a shock in the labor participation rate affects migratory movements mainly through increased labor market tightness. A positive (relative) shock in the regional human capital endowment attracts net inflows mainly through the link between human capital accumulation and productivity growth as suggested by theoretical growth theory.

Moreover, the dynamic simultaneous nature of our PVAR(1) also allows to work out the feedback effects from migratory movements to regional labor market variables. Here we mainly find that migration has an equilibrating effect on regional labor markets in line with the neoclassical view. That is, a high level of in-migration in region i increases the region's unemployment rate relative to region j, while at the same time the net in-migration lowers regional wage rate differences (the wage in region i decreases relative to j) and thus works towards a cross-regional wage equalization. Responses of labor productivity growth and the labor participation rate with respect to migration are positive but rather small in magnitude, while the revealed effect on human capital hints at the risks of regional 'brain drain' effects for German data given that increased net out-migration flows are not neutral to the regional distribution of human capital endowment but affect the relative regional skill composition. As the analysis of impulse–response functions of the PVAR(1) shows, this deterioration of the regional human capital base (via the migration channel) is largely driven by shocks in the regional unemployment rate.

We finally use the model to analyze the evolution of the two distinct waves of East–West net out-migration up to 2006. Adopting a dummy variable approach to test for structural differences for the whole East German macro region as well as the East–West border regions compared to the German average, we find that throughout the mid-1990s East–West migratory movements did not fully react to regional labor market signals as expected from the PVAR(1) results. The latter finding supports earlier empirical evidence for German and Italian regional data. Likely explanations for this "empirical puzzle" may be seen, e.g., in huge income transfers, the possibility of high East–West commuting and initially very optimistic expectations about the speed of East–West income convergence.

However, by using a recursive estimation strategy, we find that, for subsequent periods, this relationship becomes less stable or even reversed. That is, along with the peak of a second wave of East–West migratory movements around 2001, the East German dummy turns significantly negative. Since this second wave is accompanied by a gradual fading out of macroeconomic distortions such as massive East–West transfers and a downsizing of expectations about the speed of convergence, this supports the view of repressed migration flows out of East Germany for that period given the overall weak labor market and macroeconomic performance. Towards the sample end in 2006, the dummy turns insignificant, indicating that migratory movements between East and West Germany largely react to regional labor market signals. This latter result may be taken as a first hint at an advancing labor market integration between the two macro regions.

Appendix A: Testing for Instrument Validity in the Migration Equation

The inclusion of valid instrumental variables (IV) in the regression model is of vital importance for consistency of the obtained results. A statistical tool to guide IV selection is the Sargan (1958)/Hansen (1982) overidentification test (also denoted as J-statistic). As pointed out by Bowsher (2002) and Roodman (2009), one has to carefully interpret Hansen's J-statistic since it has shrinking power with increasing number of instruments. That is, numerous instruments can over fit the instrumented variables, failing to expunge their endogenous components and biasing coefficient estimates towards those from non-instrumented estimators. In a series of Monte Carlo simulations Bowsher (2002) shows that the J-statistic based on the full instrument set essentially never rejects the null when T becomes too large for a given value of N. The author proposes to reduce the number of lag length employed for estimation in order to improve the size properties of the test.

Alternatively, Roodman (2009) argues in favor of using 'collapsed' instruments, which has the potential advantage of retaining more information since no lags are dropped as instruments. This strategy is equivalent to imposing certain coefficient homogeneity assumptions on the IV set and thus makes the instrument count linear in T. The author further shows that for cases where the 'no conditional heteroscedasticity' (NCH) assumption holds, the simple Sargan (1958) statistic may be used as an appropriate indicator to check for IV consistency, which does not suffer does not suffer from the above problem since it does not depend on an estimate of the optimal weighting matrix in the two-step GMM approach. Nevertheless, the problem with the Sargan statistic is that the latter performs weak for non normal errors. Our solution to these shortcomings is to combine both test statistics in an IV downward testing approach from the full instrument set to an specification that satisfies both the Sargan as well as Hansen's J-statistic.

Our resulting IV downward testing approach using the long-run migration equation as an example is shown in Table 2.5. In the first column of the table we apply

Table 2.5 Downward testing approach for instrument validity in PVAR model

Dep. var.	r.h.s. var.	I	II	III
$nm_{ij,t}$	$nm_{ij,t-1}$	0.37^{***}	0.28^{***}	0.43^{***}
		(0.039)	(0.056)	(0.052)
$nm_{ij,t}$	$\widetilde{wr}_{ij,t-1}$	0.61^{***}	0.37^{***}	0.49^{***}
		(0.095)	(0.110)	(0.144)
$nm_{ij,t}$	$\widetilde{ur}_{ij,t-1}$	-0.14^{***}	-0.23^{***}	-0.12^{**}
		(0.034)	(0.057)	(0.051)
$nm_{ij,t}$	$\Delta\widetilde{ylr}_{ij,t-1}$	0.61^{***}	0.43^{***}	0.66^{***}
		(0.052)	(0.074)	(0.073)
$nm_{ij,t}$	$\tilde{q}_{ij,t-1}$	0.12	−0.09	0.02
		(0.110)	(0.307)	(0.277)
$nm_{ij,t}$	$\widetilde{hc}_{ij,t-1}$	-0.02^{**}	-0.02^{*}	-0.02^{*}
		(0.011)	(0.014)	(0.013)
$nm_{ij,t}$	D_{NIE}	-0.21^{***}	-0.22^{**}	-0.18^{***}
		(0.053)	(0.090)	(0.055)
(...)				
F-test		219.4	61.18	109.73
		(0.00)	(0.00)	(0.00)
RMSE		0.214	0.238	0.204
No. of IVs		459	90	20
Sargan		1671.9	343.3	11.2
		(0.00)	(0.00)	(0.59)
Hansen J		239.9	191.3	16.7
		(0.99)	(0.00)	(0.21)
C-stat. level-eq.				7.41
				(0.28)
$\chi^2_{Het}(7)$				2.18
				(0.94)
$\chi^2_m(7)$				10.33
				(0.17)

Note: Standard errors are computed based on Windmeijer's (2005) finite-sample correction. χ^2_{Het}: Heteroscedasticity test based on the regression of squared residuals on squared fitted values. χ^2_m: Hausman $|m|$-statistic based on the absolute values as discussed in Schreiber (2007)
*Denote statistical significance at the 10% level **Denote statistical significance at the 5% level
***Denote statistical significance at the 1% level

the full set of available instruments according to (2.10) and (2.14). Among lagged net migration ($nm_{ij,t-1}$) as right hand side regressor we include regional differences in real wages ($\widetilde{wr}_{ij,t-1}$), unemployment rates ($\widetilde{ur}_{ij,t-1}$), labor productivity growth ($\Delta\widetilde{ylr}_{ij,t-1}$), labor participation ($\tilde{q}_{ij,t-1}$) and human capital ($\widetilde{hc}_{ij,t-1}$). We also control for the distortion in the migration pattern for Lower Saxony due to German resettlers by the inclusion of a dummy variable (D_{NIE}).

We see that the Sargan (1958) and Hansen (1982) overidentification tests yield clearly contrasting testing results: While Hansen's J-statistic does not reject the null hypothesis of the joint validity of the included IV set, the Sargan statistic casts serious doubts on the consistency of the latter. As discussed above, the reason for the divergence in the testing results is the huge number of instruments employed for estimation (a total of 459), which lowers the power of the J-statistic. The huge number of potentially available instruments in the SYS-GMM approach is due to the exponential growth of instrumental variables with increasing time horizon T according to the standard moment condition in (2.10). In order to minimize this problem, in column 2 of Table 2.5 we therefore employ the collapsed IV set, which reduces the number of instruments to 90.

For this specification the Hansen J-statistic now clearly rejects the null of joint validity of the IV set and is thus in line with the Sargan (1958) statistic. This result underlines the point raised by Bowsher (2002) and Roodman (2009) that the J-statistic has no power with increasing number of instruments, while the Sargan test still has. Finally, based on the collapsed IV set we further reduce the number of instruments using a C-statistic based algorithm, which is able to subsequently identify those IV subsets with the highest test results (see Mitze 2009, for details). This gives us a model with a total of 20 instruments, which passes both the Sargan and Hansen J-stat. criteria as reported in Table 2.5.

The regression results show that the estimated parameter coefficients are qualitatively in line with the full IV set specification in column 1. Moreover, the downward tested model also shows to have the smallest RMSE and does not show any sign of heteroscedasticity in the residuals.[17] We finally apply the same estimation strategy for the whole PVAR(1) system, which reduces the number of instruments to 222 (out of a maximum of 2382 in the full 'uncollapsed' IV case).

Appendix B: Impulse–Response Functions and In-Sample PVAR(1) Predictions for East–West Net Migration

[17] For the latter, we use the approach outlined in Wooldridge (2002) and run a regression of the squared residuals on the squared fitted values.

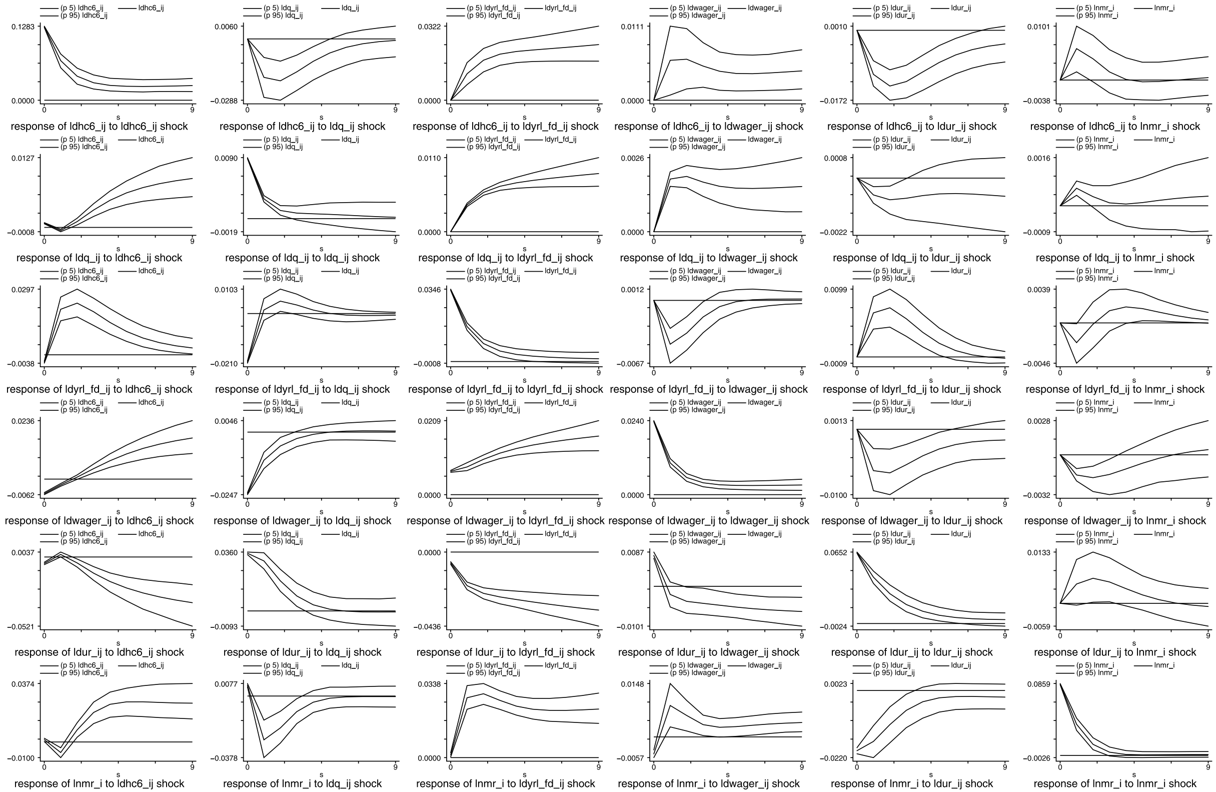

Fig. 2.8 Impulse–responses for PVAR(1), $\widetilde{hc}_{ij,t}, \tilde{q}_{ij,t}, \Delta\widetilde{ylr}_{ij,t}, \widetilde{wr}_{ij,t}, \tilde{ur}_{ij,t}, nm_{ij,t}]$. *Note*: With $nm_{ij,t}$ = lnmr_i, $\tilde{ur}_{ij,t}$ = ldur_ij, $\widetilde{wr}_{ij,t}$ = ldwager_ij, $\Delta\widetilde{ylr}_{ij,t}$ = ldyrl_fd_ij, $\tilde{q}_{ij,t}$ = ldq_ij, $\widetilde{hc}_{ij,t}$ = ldhc6_ij

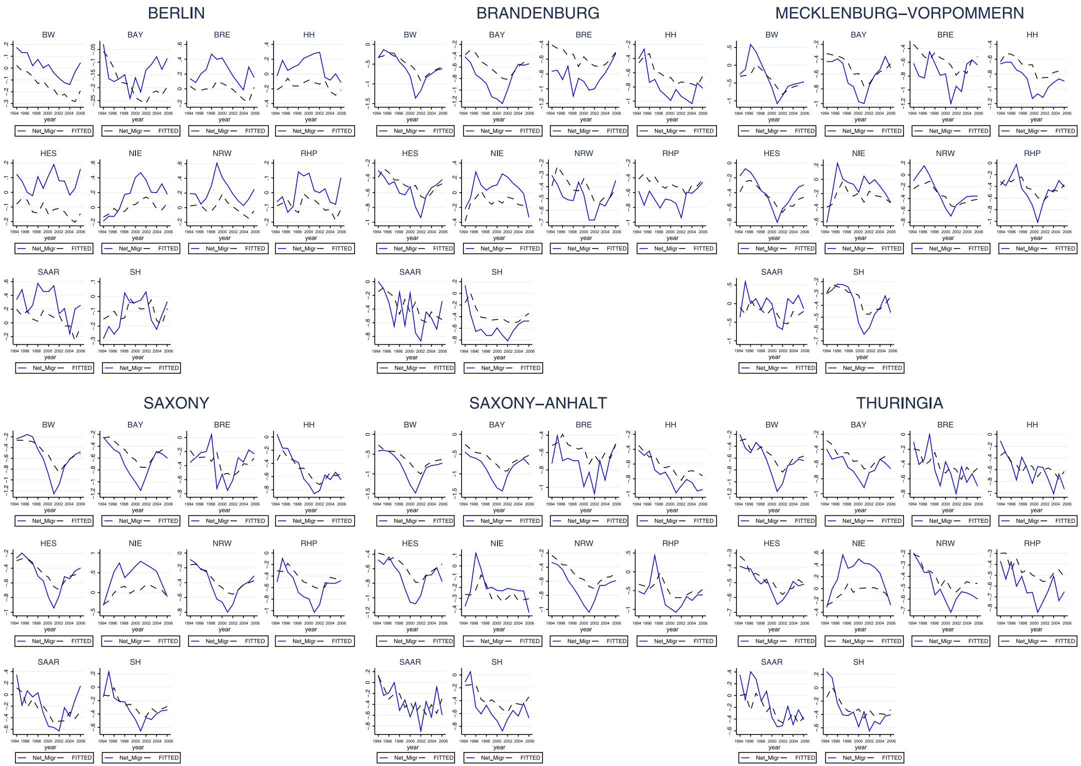

Fig. 2.9 Actual and fitted net migration between East and West German state pairs. *Note*: For details about the computation see text. BW = Baden-Württemberg, BAY = Bavaria, BRE = Bremen, HH = Hamburg, HES = Hessen, NIE = Lower Saxony, NRW = North Rhine-Westphalia, RHP = Rhineland-Palatine, SAAR = Saarland, SH = Schleswig-Holstein

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Chapter 3
Testing the Neoclassical Migration Model: Overall and Age-Group Specific Results for German Regions

3.1 Introduction

There are many theories aiming to explain, why certain people migrate and others do not. However, the neoclassical model remains still the standard workhorse specification for analyzing internal and external migration rates at regional, national and international levels. The model places special emphasis on the labor market dimension of migration and basically relates migration-induced population changes to the relative income (or wage) and employment situation found in the regions of origin and destination.

In its response, migration works as an equilibrating mechanism for balancing differences among regions with respect to key labor market variables since higher in-migration in a region is expected to reduce the regional wage level due to an increase in labor supply. From the perspective of economic policy making, the empirical implications of the neoclassical migration model are important in order to assess whether labor mobility can act as an appropriate adjustment mechanism in integrated labor markets facing asymmetric shocks. Though the neoclassical migration model is widely used as a policy simulation and didactic tool, international empirical evidence so far has provided rather mixed results.

In this paper, we therefore aim to check the validity of the neoclassical migration model using a panel of 97 German regions for the period 1996–2006. We are especially interested in taking a closer look at the role played by time dynamic adjustment processes driving the internal migration patterns. We also aim to identify the role of additional factors besides key labor market signals as well as regional amenities in explaining migratory movements. Finally, we focus on the heterogene-

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Jointly with Janina Reinkowski. Ifo Institute for Economic Research, Department Social Policy and Labour Markets, e-mail: Reinkowski@ifo.de.

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ity of the adjustment processes taking place when migration flows are disaggregated by age groups.

The remainder of the chapter is organized as follows: Sect. 3.2 sketches the theoretical foundations of the neoclassical migration model. Building on the theoretical underpinnings, Sect. 3.3 discusses the estimation approach with a special focus on dynamic panel data models. Section 3.4 then presents a selected literature review for empirical studies dealing with the determinants of internal migration flows. Section 3.5 describes the data used and displays stylized facts for German internal migration and labor market trends. Section 3.6 presents the empirical results for the total sample as well as different age groups. Apart from an economic interpretation of the estimation coefficients obtained, we also carefully look at any model misspecification such as cross-sectional dependence in the error terms. Section 3.7 concludes the chapter.

3.2 The Neoclassical Migration Model

Given the complex nature of the decision making process faced by individuals, there is a large variety of theoretical models available to explain the actual migration outcome. These models may either be classified as micro- or macroeconomic in nature. Given the scope of this paper, in the following we focus on the latter class which particularly addresses the labor market dimension of migratory flows. However, as for many macro relationships, the neoclassical migration model is also grounded on solid microeconomic foundations. Its derivation starts from a lifetime expected income (utility) maximization approach as specified in the classical work on the human capital model of migration (see Sjaastad 1962). The human capital model in fact views the process of migration as an investment decision, where the returns to migration in terms of higher wages associated with a new job should exceed the costs involved in moving.

Relaxing the assumption that prospective migrants have perfect information about the wage rates and job availabilities among all potential locations involved in their decision making process, Todaro (1969) proposed a model framework where migrants discount wages by the probability of finding a job in alternative regions. Throughout the decision making process, each individual compares the expected (rather than observed) income level he would obtain if were to stay in his home region (i) with the expected income we would obtain in the alternative region (j) and further accounts for 'transportation costs' of moving from region i to j.

Harris and Todaro (1970) further formalize this idea. The authors set up a model where the expected income from staying in the region of residence Y^E_{ii} is a function of the wage rate or income in region i (Y_i) and the probability of being employed $(Prob(EMP_i))$. The latter in turn is assumed to be a function of the unemployment rate in region i (U_i) and a set of further economic and non-economic determinants (X_i). The same setup holds for region j accordingly. Taking costs of moving from region i to j into account (C_{ij}), the individual's decision will be in favor of moving to region j if

$$Y_{ii}^{E} < Y_{ij}^{E} - C_{ij}, \tag{3.1}$$

where $Y_{ii}^{E} = f(Prob(EMP_i), Y_i)$ and $Y_{ij}^{E} = f(Prob(EMP_j), Y_j)$. The potential migrant weights the proposed wage level in the home and target regions with the individual probability of finding employment. Using this information, we can set up a model for the regional net migration rate (NM_{ij}) defined as regional in-migration flows to i from j relative to out-migration flows from i to j (possibly normalized by the regional population level), which has the following general form:

$$INM_{ij} - OUTM_{ij} = NM_{ij} = f(Y_i, Y_j, U_i, U_j, X_i, X_j, C_{ij}). \tag{3.2}$$

With respect to the theoretically motivated signs of the explanatory variables, the model predicts that an increase in the home region wage rate (or, alternatively, the real income level) *ceteris paribus* leads to higher net migration inflows, while a wage rate increase in region j results in a decrease of the net migration rate. On the contrary, an increase in the unemployment rate in region i (j) has negative (positive) effects on the bilateral net migration from i to j. The costs of moving from i to j are typically expected to be an impediment to migration and are negatively correlated with net migration as:

$$\frac{\partial NM_{ij}}{\partial Y_i} > 0; \qquad \frac{\partial NM_{ij}}{\partial Y_j} < 0; \qquad \frac{\partial NM_{ij}}{\partial U_i} > 0; \qquad \frac{\partial NM_{ij}}{\partial Uj} < 0; \qquad \frac{\partial NM_{ij}}{\partial C_{ij}} < 0. \tag{3.3}$$

Core labor market variables may nevertheless not be sufficient to fully predict regional migration flows. We may extend the model by further driving forces of migration such as human capital, the regional competitiveness, housing prices, population density and environmental conditions, among others (see e.g. Napolitano and Bonasia 2010, for an overview). For notational purposes, in the following we refer to the neoclassical migration model solely focusing on labor market conditions as the 'baseline' specification, while the 'augmented' specification also controls for regional amenities and further driving forces such as the regional skill level, population density and commuting flows as a substitute for migratory movements.

The likely impact of additional variables in the augmented neoclassical framework can be sketched as follows. Taking human capital as an example, it may be quite reasonable to relax the assumption of the Harris–Todaro model that an uneducated laborer has the same chance of getting a job as an educated laborer. Instead, the probability of finding a job is also a function of the (individual but also region specific) endowment with human capital (*HK*). The same logic holds for regional competitiveness (*INTCOMP*). Here, we expect that regions with a high competitiveness are better equipped to provide job opportunities than regions lagging behind (where regional competitiveness may e.g. be proxied by the share of foreign turnover relative to total turnover in sectors with internationally tradable goods). For population density (*POPDENS*), we expect a positive impact of agglomeration forces on net flows through an increased possibility of finding a job, given the relevance of spillover effects e.g. from a large pooled labor market. Thus, the probability of finding employment in region i in the augmented neoclassical migration model takes the following form:[1]

$$Prob(EMP_i) = f[U_i, HK_i, INTCOMP_i, POPDENS_i],$$
$$\text{with} \quad \frac{\partial NM_{ij}}{\partial HK_i} > 0; \quad \frac{\partial NM_{ij}}{\partial INTCOMP_i} > 0; \quad \frac{\partial NM_{ij}}{\partial POPDENS_i} > 0. \tag{3.4}$$

Moreover, we also carefully account for alternative adjustment mechanisms such as interregional net commuting flows to restore the inter-regional labor market equilibrium along with migratory movements. As Alecke and Untiedt (2001) point out, the theoretical as well as empirical literature with respect to interregional commuting (different from intraregional commuting) is rather scarce. According to Evers (1989), theoretical models of interregional commuting base the commuting decision on driving forces similar to those outlined in the migration framework. We thus expect that these flows are negatively correlated with net in-migration after controlling for common determinants such as regional income differences.

Finally, regional amenities are typically included as a proxy variable for (unobserved) specific climatic, ecological or socio-economic conditions in a certain region. According to the amenity approach regional differences in labor market signals then only exhibit an effect on migration after a critical threshold has been passed. Since in empirical terms it is often hard to operationalize amenity relevant factors, Greenwood et al. (1991) proposed to test the latter effect by the inclusion (macro-)regional dummy variables in the empirical model. For the long run net migration equation, amenity-rich regions then should have dummy coefficients greater than zero, indicating that those regions exhibit higher than average in-migration rates as would be expected after controlling for regional labor market and macroeconomic differences.

3.3 Econometric Specification

3.3.1 Functional Form of the Empirical Migration Equation

For empirical estimation of the neoclassical migration model we start from its baseline specification as, e.g., applied by Puhani (2001) and set up a model for the net migration rate as:

$$\left(\frac{NM_{ij,t}}{POP_{i,t-1}}\right) = A_{i,t}\left(\frac{U_{i,t-1}^{\alpha_1} Y_{i,t-1}^{\alpha_2}}{U_{j,t-1}^{\alpha_3} Y_{j,t-1}^{\alpha_4}}\right), \tag{3.5}$$

where net migration rate between i and j is defined as regional net balance NM for region i relative to the rest of the country j, POP is the region's i population level, t is the time dimension.[2] A is a (cross-section specific) constant term.

[1]The opposite effect on NM_{ij} holds for an increase in $HK \uparrow$, $INTCOMP \uparrow$ and $POPDENS \uparrow$ in region j.

[2]See e.g. Maza and Villaverde (2004) for a similar definition of the dependent variable.

In the empirical literature, a log-linear stochastic form of the migration model in (3.5) is typically chosen, where lower case variables denote logs and $nmr_{ij,t} = \log(NM_{ij,t}/POP_{i,t-1})$ as

$$nmr_{ij,t} = \alpha_0 + \alpha_1 y_{i,t-1} + \alpha_2 y_{j,t-1} + \alpha_3 u_{i,t-1} + \alpha_4 u_{j,t-1} + \alpha_5 \mathbf{X} + e_{ij,t}, \tag{3.6}$$

where $e_{ij,t}$ is the model's error term. Taking into account that migration flows typically show a degree of persistence over time, we augment (3.6) by including one-period lagged values of net migration

$$nmr_{ij,t} = \beta_0 + \beta_1 nmr_{ij,t-1} + \beta_2 y_{i,t-1} + \beta_3 y_{j,t-1} + \beta_4 u_{i,t-1} + \beta_5 u_{j,t-1} + \beta_6 \mathbf{X} + e_{ij,t}. \tag{3.7}$$

The inclusion of a lagged dependent variable can be motivated by the existence of social networks in determining internal migration flows over time. Rainer and Siedler (2009), for example, find for German micro data that the presence of family and friends is indeed an important predictor for migration flows in terms of communication links, which may result in a gradual adjustment process over time for migration flows out of a particular origin to a destination region.

To account for the role played by timely adjustment processes in the endogenous variable, in the context of panel data models specific estimation techniques based on instrumental variables have to be applied. Besides the problem arising from a dynamic model specification, these techniques, in combination with an appropriate lag selection for the further explanatory variables, it may also help to minimize the fundamental endogeneity problem in this model setup, which arises from a two-way causality between internal migration and regional labor market variables. We give a detailed discussion of the latter point throughout the outline of the applied estimation techniques in the following.

Finally, in applied work one typically finds a restricted version of (3.7) where net migration is regressed against regional differences of explanatory variables of the form (see, e.g., Puhani 2001)

$$nmr_{ij,t} = \gamma_0 + \gamma_1 nmr_{ij,t-1} + \gamma_2 \tilde{y}_{ij,t-1} + \gamma_3 \tilde{u}_{ij,t-1} + \gamma_4 \mathbf{X} + e_{ij,t}, \tag{3.8}$$

where $\tilde{x}_{ij,t}$ for a variable $x_{ij,t}$ denotes $\tilde{x}_{ij,t} = x_{i,t} - x_{j,t}$. The latter specification implies the following testable restrictions

$$\beta_2 = -\beta_3, \tag{3.9}$$

$$\beta_4 = -\beta_5. \tag{3.10}$$

3.3.2 Choice of Estimation Technique and Model Misspecification Tests

For estimation purposes we then have to find an appropriate estimator that is capable of handling the above described empirical setup. Given the dynamic nature of the neoclassical migration model in (3.7), we can write the specified form in terms of a more general dynamic panel data model as (in log-linear specification):

$$y_{i,t} = \alpha_0 + \alpha_1 y_{i,t-1} + \sum_{j=0}^{k} \beta_j' X_{i,t-j} + u_{i,t}, \quad \text{with: } u_{i,t} = \mu_i + \nu_{i,t}, \tag{3.11}$$

again $i = 1, \dots, N$ (cross-sectional dimension) and $t = 1, \dots, T$ (time dimension). $y_{i,t}$ is the endogenous variable and $y_{i,t-1}$ is one period lagged value. X_i is the vector of explanatory time-varying and time invariant regressors, $u_{i,t}$ is the combined error term, where $u_{i,t}$ is composed of the two error components μ_i as the unobservable individual effects and $\nu_{i,t}$ is the remainder error term. Both μ_i and $\nu_{i,t}$ are assumed to be i.i.d. residuals with standard normality assumptions.

There are numerous contributions in the recent literature on how to estimate a dynamic model of the above type, which especially deal with the problem introduced by the inclusion of a lagged dependent variable in the estimation equation and its built-in correlation with the individual effect: that is, since y_{it} is a function of μ_i, also $y_{i,t-1}$ is a function of μ_i and thus $y_{i,t-1}$ as right-hand side regressor in (3.11) is likewise correlated with the combined error term. Even in the absence of serial correlation of ν_{it} this renders standard λ-class estimators such as OLS, the fixed effects model (FEM) and the random effects model (REM) inconsistent (see e.g. Nickell 1981; Sevestre and Trognon 1995 or Baltagi 2008, for an overview).

Next to direct approaches aiming to correct for the bias of the FEM (see e.g. Kiviet 1995; Everaert and Pozzi 2007, and the related literature for analytical or bootstrapping-based correction factors), the most widely applied approaches of dealing with this kind of endogeneity typically applies instrumental variable (IV) and generalized methods of moments (GMM) based techniques. While the first generation of models used transformations in first differences, latter extensions also account for the information in levels, when setting up proper estimators. A common tool is the system GMM estimator by Blundell and Bond (1998) as weighted average of first difference and level GMM.

Especially the latter estimators are a good candidate to simultaneously handle the problem arising from the inclusion of the lagged migration variable in our empirical model and the fundamental endogeneity problem induced by two-way causality between migration and labor market variables. In our case, the combination of an appropriate lag selection for the right-hand side regressors combined with the IV approach may do so. That is, since we include labor market variables with a lag structure in (3.7), by definition there cannot be any direct feedback effect from $nmr_{ij,t}$ to labor market variables. However, since $nmr_{ij,t-1}$ enters contemporaneously with respect to the latter, there is still the risk of two-way interdependencies due to the dynamic setting of the model. We minimize these potential risks of any endogeneity bias by instrumenting $nmr_{ij,t-1}$ with its lagged values so that the possibility of feedback effects from migration responses to labor market changes as source of estimation bias is limited. This should lead to consistent estimates of the coefficients for the explanatory variables.[3]

[3]Of course, a full account of the simultaneity problem may call for a system approach that is also likely to increase the estimation efficiency if there are significant cross-correlations in the error

We are then also particularly interested in testing for the appropriateness of the chosen IV approach and apply test routines that account for the problem of many and/or weak instruments in the regression (see e.g. Roodman 2009). Moreover, as it is typically the case with regional data, we are especially aware of the potential bias induced by a significant cross-sectional dependence in the error term of the model. There are different ways to account for such error cross-sectional dependences implying $\mathrm{Cov}(\nu_{i,t}\nu_{j,t}) \neq 0$ for some t and $i \neq j$ (see Sarafidis and Wansbeek 2010).

Besides the familiar spatial econometric approach, which assumes certain distance decay in spatial dependence, recently the common factor structure approach has gained considerable attention. The latter specification assumes that the disturbance term contains a finite number of unobserved factors that influence each individual cross-section separately. The common factor model approach is based on the concept of strong cross-sectional dependence, which assumes that all regions, either symmetrically or asymmetrically, are affected rather than just those nearby. Common examples are for instance, regional adjustment processes to common macroeconomic shocks. We introduce a common factor structure for the error term according to (3.11) in the following way:

$$u_{i,t} = \mu_i + \nu_{i,t}, \quad \nu_{i,t} = \sum_{m=1}^{M} \phi_{m,i}\mathbf{f}_{m,t} + \epsilon_{i,t}, \tag{3.12}$$

where $\mathbf{f}_{m,t} = (f_{1,t}, \ldots, f_{M,t})'$ denotes an $M \times 1$ vector of individual-invariant time-specific unobserved effects, $\phi_i = (\phi_{1,i}, \ldots, \phi_{M,i})'$ is an $M \times 1$ vector of factor loadings and $\epsilon_{i,t}$ is a pure idiosyncratic error component with zero mean and constant variance. Cross-sectional dependence in turn leads to inconsistent estimates if regressors are correlated with the unspecified common variables or shocks. There are different proposals in the literature on how to account for unobserved factors.

For dynamic panel estimators with short time dimension, Sarafidis and Robertson (2009) propose applying time-specific demeaning which alleviates the problem of parameter bias if the variance of the individual factor loadings for the common factor models is small. Alternatively, if the impact of the common factor varies considerably by cross-sections, there are different estimation techniques that account for this type of cross-sectional dependence by using cross-section averages of the dependent and independent variables as additional regressors (see e.g. Pesaran 2006).

Recently, various testing procedures have been developed to check for the presence of cross-sectional dependence. Among the most commonly applied routines is Pesaran's (2007) extension to the standard Breusch and Pagan LM test. The so-called Cross-Section Dependence (CD) test is based on the pairwise correlation coefficient of residuals from a model specification that ignores the potential presence of cross-sectional dependence. However, as Sarafidis and Wansbeek (2010) point out, the CD-Test has the weakness that it may lack power to detect the alternative hypothesis under which the sign of the elements of the error covariance matrix is

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terms for functional forms of the migration and labor market variable equations. However, a fully specified system approach goes beyond the scope of this paper.

alternates (thus for positive and negative correlation in the residuals, e.g. for factor models with zero mean factor loadings).

Moreover, the test statistic requires normality of the residuals. Sarafidis et al. (2009) propose an alternative testing procedure that does not require normality and is valid for fixed T and large N. The testing approach, which is designed for the Arellano and Bond (1991) and Blundell and Bond (1998) GMM estimators, is based on the Diff-in-Hansen test for overidentifying restrictions. The latter is also known as the C-statistic and is defined according to Eichenbaum et al. (1988) as the difference between two Sargan (1958)/Hansen (1982) J-statistics for an unrestricted and restricted IV/GMM-model. The aim of the test is to examine whether there is still (heterogeneous) cross-sectional dependence in the residuals after time-specific demeaning in the logic of Sarafidis and Robertson (2009). The test has the following form:

$$C_{CD\text{-}GMM} = (S_F - S_R) \xrightarrow{d} \chi^2_{h_d}, \tag{3.13}$$

where h_d is the number of degrees of freedom of the test statistic as difference between the set of instruments (number of moment conditions) in the full model (S_F) and the restricted model (S_R), where the GMM model has either the Arellano–Bond or the Blundell–Bond form augmented by time-specific dummy variables. The corresponding null hypothesis of the Sargan's difference-test tests is that there is homogeneous cross-sectional dependence in the model versus the alternative of heterogeneous cross-sectional dependence. If only homogeneous cross-sectional dependence is present, the inclusion of time-specific dummies variables is sufficient to remove any bias in the estimation approach, see e.g. Sarafidis and Robertson (2009).[4]

3.4 What Does the Empirical Literature Say?

Testing for the empirical validity of the neoclassical migration model yields rather mixed results, when looking at recent empirical evidence for European data. Here, regional (un-)employment disparities are often shown to be important factors in determining migratory flows. On the contrary, the influence of regional wage or income levels is difficult to prove in many empirical examinations (see e.g. Pissarides and McMaster 1990, as well as (Jackman and Savouri 1992) for British regions; Westerlund 1997, for inter-regional migration in Sweden, Devillanova and Garcia-Fontes 2004, for Spain). For the Italian case, Daveri and Faini (1999) show that the regional wage level corresponds to the theoretically expected signal for the gross outward migration from southern to northern regions. Similar results are found in Fachin (2007).

[4]The restricted (sub-)set of moment conditions thereby only includes instruments from regressors in the vector $X_{i,t}$ (according to (3.11)) that remain strongly exogenous in the sense that their factor loadings are mutually uncorrelated with the cross-section specific parameter of the common factor. Sarafidis et al. (2009) propose to likewise test for the exogeneity of a subset of regressors by means of the standard Sargan/Hansen test for overidentifying restrictions in a first step.

Napolitano and Bonasia (2010) show that although the coefficients for Italian labor market variables in the neoclassical migration model have the expected sign, due to the complexity of the internal migration process, the baseline Harris–Todaro approach neglects important variables such as agglomeration forces measured by population density and human capital. The latter variables are also found to be significant in addition to the standard labor market variables in an inter-regional migration model for the Polish transition process (see Ghatak et al. 2008). This indicates that the augmented migration model may be in order.

Turning to the case of German interregional migration, Decressin (1994) examined gross migration flows for West German states up to 1988. His results show that a wage increase in one region relative to others causes a disproportional rise in the gross migration levels in the first region. On the other hand, a rise in the unemployment in a region relative to others disproportionally lowers the gross migration levels. Decressin does not find a significant connection between bilateral gross migration and regional differences in wage level or unemployment when purely cross-sectional estimates are considered.

Difficulties in proving a significant influence of regional wage decreases on the migratory behavior within Germany are also found in earlier empirical studies based on micro-data directly addressing the motivation for individual migratory behavior in Germany. Among these are Hatzius (1994) for the West German states, and Schwarze and Wagner (1992), Wagner (1992), Burda (1993) and Büchel and Schwarze (1994) for East Germany. Subsequent studies succeed in qualifying the theoretically unsatisfactory result of an insignificant wage influence. Schwarze (1996) shows that by using the expected wage variables instead of the actual ones, the wage drop between East German and West German states has a significant influence on the migratory behavior.[5] In a continuation of Burda (1993), Burda et al. (1998) also indicates a significant non-linear influence on household income.

Contrary to earlier evidence, in recent macroeconomic studies with an explicit focus on intra-German East–West migration flows, regional wage rate differentials are broadly tested to significantly affect migration flows (see, e.g., Parikh and Van Leuvensteijn 2003; Burda and Hunt 2001; Hunt 2006, as well as Alecke et al. 2010). The study of Parikh and Van Leuvensteijn (2003) augments the core migration model with regional wage and unemployment differentials as driving forces of interregional migration by various indicators such as regional housing costs, geographical distance and inequality measures. For the sample period 1993 to 1995, the authors find a significant non-linear relationship between disaggregated regional wage rate differences and East–West migration (of a U-shaped form for white-collar workers and of inverted U-form for blue-collar workers), while unemployment differences showed to be insignificant. The relationship between income inequality and migration did not turn out to be strong.

[5] This result is also confirmed by Brücker and Trübswetter (2004). The latter study also focuses on the role of self-selection in East–West migration, finding that East–West migrants receive a higher individual wage compared to their non-migrating counterparts after controlling for the human capital level.

According Burda and Hunt (2001), wage rate differentials and especially the fast East–West convergence are also a significant indicator in explaining the state-to-state migration patterns observed. Using data from 1991 to 1999, the authors find that the decline in East–West migration starting from 1992 onwards can almost exclusively be explained by wage differentials and the fast East–West wage convergence, while unemployment differences do not seem to play an important part in explaining actual migration trends. The study by Hunt (2006) comes closest to the research focus in this paper. The author also estimates the migration response to labor market signals by age groups and finds that young potential emigrants are more sensitive to wages than older age cohorts. At the same time young age groups are found to be less sensitive to unemployment levels in the origin region. Hunt (2006) argues that the latter finding is likely to drive the migration pattern pooled over all age groups and thus gives a motivation for the dominance of wage rate signals in aggregate data as, e.g., reported by Burda and Hunt (2001).

Alecke et al. (2010) apply a Panel VAR to analyze the simultaneous impact of labor market variables to migration and vice versa for German federal states between 1991 and 2006. The results broadly support the neoclassical migration model and show that migration itself has an equilibrating effect on labor market differences. The authors also find evidence for structural differences between the German West and East macro regions in the migration equation, which is similar to findings for an Italian ‘empirical puzzle’ with a distinct North–South division in terms of the magnitude of migration responses to labor market signals (see e.g. Fachin 2007; Etzo 2007).

The recent results for Germany also show that the specific time period used for estimation may have a significant impact on the estimation results. Especially for the first years after German re-unification several structural breaks are in order that may partly explain the results between earlier and recent contributions with respect to German internal migration. However, except for Alecke et al. (2010), none of the empirical papers take into account recent sample observations incorporating information about the second wave of strong East–West out-migration around the year 2001. The allocation of higher weights to recent sample observations may in turn minimize the risk of biasing the results in the light of distinct macro regional structural breaks.[6]

3.5 Data and Stylized Facts

We use the heterogeneous findings in the international and German empirical literature regarding the neoclassical migration model as a starting point for an updated regression approach based on German spatial planning units between 1996

[6] In this paper we account for regional and macro regional results by including East German and state level fixed effects. However, future work should also explicitly test for the poolability of the data for regional subgroups in a partial clustering framework.

and 2006. For empirical estimation we use regional data for the 97 German Spatial Planning Regions (so called *Raumordnungsregionen*) as the level of analysis for spatial migration processes within Germany (see e.g. Bundesinstitut für Bau-, Stadt-, und Raumforschung, 2010, for details about the concept of Spatial Planning Regions).[7]

We use a set of variables comprising regional net migration, population, real income, unemployment rate, human capital endowment, international competitiveness of regions and commuting flows. The latter variable has been included to account for an alternative adjustment mechanism to balance labor market disequilibria. Human capital is defined as the percentage share of regional employment with a university degree (including universities of applied science) in total employment covered by the social security system (*sozialversicherungspflichtig Beschäftigte*).[8] We also include two sets of dummy variables: 1) Binary dummy variables for the 16 federal states to capture macro regional differences (see, e.g., Suedekum 2004). This may be especially important to account for structural differences between West and East Germany (see, e.g., Alecke et al. 2010, for recent findings); 2) Binary dummy variables for different regional settlement types ranging from metropolitan agglomerations to rural areas (in total 7 different categories based on their absolute population size and population density). As Napolitano and Bonasia (2010) point out, variables measuring population density may be an important factor in explaining the regional amenities. Variable definitions and descriptive statistics are provided in Tables 3.1, 3.2 and 3.3.

To highlight regional and macro-regional differences for net migration and explanatory variables, Fig. 3.1 visualizes spatial differences for the sample means of net in-migration and labor market variables for the period 1996–2006. Net in-migration flows are categorized into labor force relevant age groups between 18 and 65 years as well as non-labor force relevant age groups. For labor force migration, the figure shows that throughout the sample period the East German regions on average lost a considerable fraction of their population levels through net out-migration. Exceptions are the economic core regions around Berlin/Brandenburg and in the south-west of Saxony. Also, the Western regions along the border to East Germany experienced net outflows. On the other hand, the northern West German regions around the urban agglomerations Hamburg and Bremen are among the net recipient regions as well as the western agglomerated regions in the Rhineland (around the metropolitan areas Cologne and Düsseldorf) and the southern West German regions in Baden Württemberg and Bavaria.

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[7] We restrict our estimation approach to this period since regional boundaries of the German Spatial Planning Regions changed before and after, which may introduce a measurement problem that is likely to bias our empirical results.

[8] We also checked for the sensitivity of the results, when using composite indicators of human capital as discussed by Dreger et al. (2009), accounting for human capital potential (measured in terms of high school graduates with university qualification per total population between 18–20 years) as well as science and technology related indicators (e.g., patent intensity). The results did not change.

Table 3.1 Variable definition and data sources

Variable	Description	Source
NM	Net migration defined as in- minus out-migration	Destatis (2009)
NM (to 18)	Net migration of persons under 18 years	Destatis (2009)
NM (18 to 25)	Net migration of persons aged between 18 and 24	Destatis (2009)
NM (25 to 30)	Net migration of persons aged between 25 and 29	Destatis (2009)
NM (30 to 50)	Net migration of persons aged between 30 and 49	Destatis (2009)
NM (50 to 65)	Net migration of persons aged between 50 and 65	Destatis (2009)
NM (over 65)	Net migration of persons aged 65 and above	Destatis (2009)
POP	Population level	VGRdL (2009)
Y	Gross domestic product (real) per capita	VGRdL (2009)
UR	Unemployment rate	Federal Employment Agency (2009)
COMM	Net commuting level defined as in- minus out-commuting	Federal Institute for Research on Building, Urban Affairs and Spatial Development (BBSR 2009)
HK	Human capital level defined as %-share of employees with university degree relative to total employees	BBSR (2009)
INTCOMP	International competitiveness proxied by foreign turnover relative to total turnover in manufacturing industries	BBSR (2009)
EAST	Binary dummy variable for regions in East Germany	own calculation
STATE	Set of binary dummies for each of the 16 Federal States	own calculation
TIME	Set of year specific time dummies for sample period 1996 to 2006	own calculation
SETTLE	Set of binary dummies for types of settlement structure with: *Type 1*: Highly agglomerated area with regional urban center above 100.000 persons and population density above 300 inhabitants/sqm *Type 2*: Highly agglomerated area with regional urban center above 100.000 persons and population density below 300 inhabitants/sqm *Type 3*: Agglomerated area with population density above 200 inhabitants/sqm *Type 4*: Agglomerated area with regional urban center above 100.000 persons and population density between 100–200 inhabitants/sqm *Type 5*: Agglomerated area without regional urban center above 100.000 persons and population density between 150–200 inhabitants/sqm *Type 6*: Rural area with population density above 100 inhabitants/sqm *Type 7*: Rural area with population density below 100 inhabitants/sqm	BBSR (2009)
i	index for region i (region in focus)	
j	index for region j (rest of the country aggregate)	
t	time index	

Table 3.2 Descriptive statistics for continuous variables in the sample

Variable	Obs.	Mean	Std. dev.	Min	Max	Unit
INM	1067	0.00	7.21	−95.90	37.01	in 1000 persons
INM (to 18)	1067	0.00	1.91	−24.41	32.41	in 1000 persons
INM (18 to 25)	1067	0.00	1.85	−12.97	15.76	in 1000 persons
INM (25 to 30)	1067	0.00	1.27	−9.93	12.42	in 1000 persons
INM (30 to 50)	1067	0.00	2.48	−30.99	8.24	in 1000 persons
INM (50 to 65)	1067	0.00	0.91	−10.61	1.82	in 1000 persons
INM (over 65)	1067	0.00	0.62	−7.05	1.23	in 1000 persons
POP	1067	848.10	607.13	226.29	3466.52	in 1000 persons
Y	1067	51.23	7.49	34.02	80.01	in 1000 Euro
UR	1067	11.84	4.94	4.37	26.18	in %
COMM	873	−33.49	37.44	−177.73	36.31	in 1000 persons
HK	873	7.30	2.71	2.88	16.81	in %
INTCOMP	946	30.05	11.42	0.82	61.12	in %

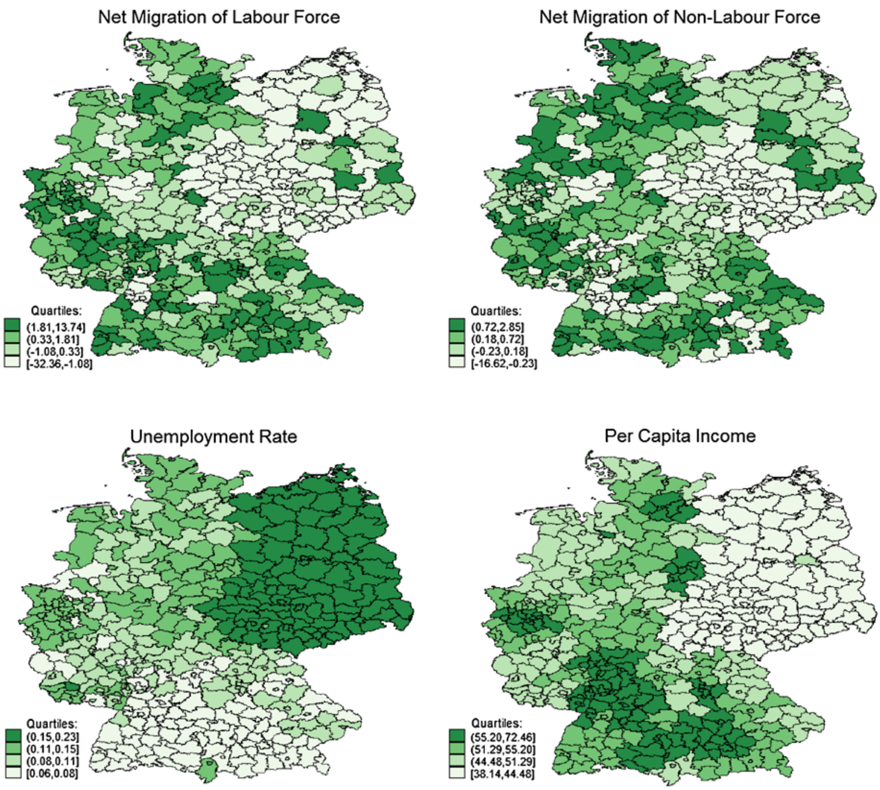

Fig. 3.1 Sample means of net migration (in 1000), unemployment rate (in %), per Capita GDP (in 1000€). *Source*: For data description see Table 3.1

Table 3.3 Descriptive statistics for binary variables in the sample

Variable	Obs.	% with $X = 1$
EAST	1067	23.7
Federal state level dummies		
BW	1067	12.4
BAY	1067	18.5
BER	1067	1.0
BRA	1067	5.2
BRE	1067	1.0
HH	1067	1.0
HES	1067	5.1
MV	1067	4.1
NIE	1067	13.4
NRW	1067	13.4
RHP	1067	5.1
SAAR	1067	1.0
SACH	1067	5.1
ST	1067	4.1
SH	1067	5.1
TH	1067	4.1
Settlement type dummies		
Type 1	1067	15.5
Type 2	1067	15.5
Type 3	1067	17.5
Type 4	1067	17.5
Type 5	1067	8.2
Type 6	1067	15.4
Type 7	1067	10.3

Note: BW = Baden-Württemberg, BAY = Bavaria, BER = Berlin, BRA = Brandenburg, BRE = Bremen, HH = Hamburg, HES = Hessen, MV = Mecklenburg-Vorpommern, NIE = Lower Saxony, NRW = North Rhine-Westphalia, RHP = Rhineland-Palatine, SAAR = Saarland, SACH = Saxony, ST = Saxony-Anhalt, SH = Schleswig-Holstein, TH = Thuringia

Looking at net migration trends for non-labor market relevant age groups, the picture is less clear. We see from Fig. 3.1 that both the north German coastal regions as well as the southern border regions gain considerable population through net in-migration. This trend may be interpreted in terms of regional amenities such as topographical advantages, which attract migration flows. The relative difference is especially observable for the East German coastal zone in Mecklenburg-Vorpommern. The spatial distribution of real per capita income and unemployment rates nevertheless show a distinct West–East division. The regions with the highest income levels for the sample period are the northern regions around Hamburg, the Western regions in the Rhineland as well as large parts of the southern states Baden-Württemberg and Bavaria. Since these regions were also found to have large net in-migration

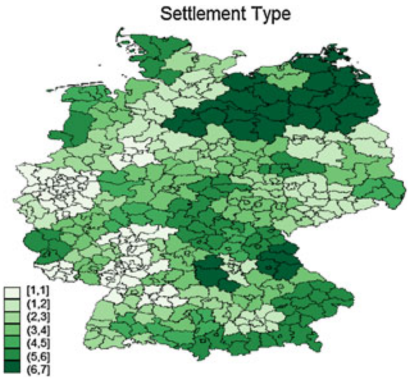

Fig. 3.2 Regional settlement structure by size of urban centers and population density. *Note*: *Type 1* = Highly agglomerated area with regional urban center above 100.000 persons and population density above 300 inhabitants/sqm. *Type 2* = Highly agglomerated area with regional urban center above 100.000 persons and population density below 300 inhabitants/sqm. *Type 3* = Agglomerated area with population density above 200 inhabitants/sqm. *Type 4* = Agglomerated area with regional urban center above 100.000 persons and population density between 100–200 inhabitants/sqm. *Type 5* = Agglomerated area without regional urban center above 100.000 persons and population density between 150–200 inhabitants/sqm. *Type 6* = Rural area with population density above 100 inhabitants/sqm. *Type 7* = Rural area with population density below 100 inhabitants/sqm. *Source*: Data from BBSR (2009)

flows (both overall as well as for the workforce relevant age-groups), this may give a first hint of the positive correlation of migration flows and regional income levels as suggested by the neoclassical migration model.

The opposite case is supposed to hold for large regional unemployment rates. Especially for the East German Spatial Planning Regions high unemployment rates seem to match with net population losses. To check the correlation of these variables more in depth, the next section presents the results of the estimation exercise. Finally, Fig. 3.2 plots the classification of regional settlement type according to the BBSR definition (see Table 3.1). Compared to the highly agglomerated areas around the urban centers Hamburg, Berlin, Stuttgart and Munich also large parts of Northrhine-Westphalia show a strong agglomeration of population. On the contrary, especially the northern parts in East Germany as well as South–Eastern regions in Bavaria are classified as rural areas. The same also holds for the middle German regions in the state-level border zones of Thuringia, Hessen and Bavaria.

3.6 Empirical Results for the Neoclassical Migration Model

3.6.1 Aggregate Findings

For the migration model of (3.7) and (3.8) we apply different static and dynamic panel data estimators. Before estimating the empirical migration model we check

Table 3.4 Results of panel unit root tests (p-values) for variables in the migration model

Test used:	p-val. LLC	Lags	p-val. IPS	Lags	p-val. CADF	Lags
	H_0: All series are non-stationary					
$nm_{ij,t}$	(0.00)	1.47	(0.03)	1.47	(0.00)	1.00
$u_{i,t}$	(0.00)	3.20	(0.00)	3.20	(0.00)	1.00
$u_{j,t}$	(0.99)	3.81	(0.00)	0.22	(0.00)	1.00
$y_{i,t}$	(0.00)	1.35	(0.00)	1.35	(0.00)	1.00
$y_{j,t}$	(0.00)	0.00	(0.00)	0.00	(0.00)	1.00
$\tilde{u}_{ij,t}$	(0.00)	3.30	(0.00)	3.30	(0.00)	1.00
$\tilde{y}_{ij,t}$	(0.00)	1.44	(0.00)	1.44	(0.00)	1.00

Note: LLC denotes the test proposed by Levin et al. (2002), IPS is the Im et al. (2003) test, CADF is the test proposed by Pesaran (2007). All unit root tests include a constant term; optimal lag length selected according to the AIC information criterion for the LLC and IPS test. The Pesaran CADF test includes one lag and a potential time trend in the estimation equation

the time series properties of the variables involved in order to avoid the risk of running a spurious regression for non-stationary variables (with moderate $T = 11$). We therefore report test results of different panel unit root tests including recently proposed methods by Levin et al. (2002) and Im et al. (2003), as well as Pesaran's (2007) CADF test. The latter approach has the advantage that it is relatively robust with respect to cross-sectional dependence in the variable, even if the autoregressive parameter is high (see e.g. Baltagi et al. 2007, as well as de Silva et al. 2009, for extensive Monte Carlo simulation evidence). As the results in Table 3.4 show, for almost exclusively all variables and test specifications the null hypothesis of non-stationarity of the series under observation can be rejected.[9] Given this overall picture of the panel unit root tests together with the theoretically motivated assumption that migration flows are transitory processes between two labor market equilibria, it seems reasonable to handle the variables as stationary processes so that we can run untransformed regressions without running the risk of spurious regression results.

For estimation we start from an unrestricted presentation of the baseline model including the core labor market variables real income (y) and unemployment rates (u) and test for parameter constraints according to (3.9) and (3.10). As the results in Table 3.5 show, for almost all model specifications the null hypothesis for equal parameter size cannot be rejected on the basis of standard Wald tests. Also, compared to the static specification in column 2, the relative root mean squared error (RMSE)

[9]It was only for the (rest of the country) aggregate of the unemployment rate that the Levin–Lin–Chu test could not reject the null of non-stationarity. However, the LLC-test rejects the null hypothesis of an integrated time series if the unemployment rate is transformed into regional differences ($\tilde{u}_{ij,t}$).

Table 3.5 Baseline specifications of the neoclassical migration model for German spatial planning regions

Dep. var.: $nm_{ij,t}$	POLS	POLS	POLS	REM	FEM	FEMc	AB-GMM	SYS-GMM
$nm_{ij,t-1}$			0.90^{***}	0.90^{***}	0.78^{***}	0.92^{***}	0.84^{***}	0.88^{***}
			(0.011)	(0.011)	(0.022)	(0.031)	(0.001)	(0.001)
$u_{i,t-1}$	-0.74^{***}							
	(0.114)							
$u_{j,t-1}$	0.64^{*}							
	(0.399)							
$\tilde{u}_{ij,t-1}$		-0.72^{***}	−0.05	−0.05	-0.32^{**}	-0.28^{*}	-0.53^{***}	-0.19^{***}
		(0.114)	(0.041)	(0.041)	(0.166)	(0.166)	(0.023)	(0.006)
$y_{i,t-1}$	0.07							
	(0.315)							
$y_{j,t-1}$	−0.14							
	(0.378)							
$\tilde{y}_{ij,t-1}$		0.07	0.12	0.12	−0.26	−0.10	0.25^{***}	0.03^{**}
		(0.314)	(0.108)	(0.112)	(0.372)	(0.374)	(0.066)	(0.014)
No. of obs.	1067	1067	1067	1067	1067	1067	1067	1067
No. of groups	97	97	97	97	97	97	97	97
No. of years	11	11	11	11	11	11	11	11
$\beta_{u_i} = -\beta_{u_j}$	(0.83)		(0.60	(0.42)	(0.11)	(0.19)	(0.00)	(0.14)
$\beta_{y_i} = -\beta_{y_j}$	(0.76)		(0.60)	(0.24)	(0.39)	(0.59)	(0.58)	(0.14)
m_1 and m_2							(0.42)/(0.24)	(0.35)/(0.24)
J-stat. Overall							Passed	Passed
C-stat. LEV-EQ								Passed
Time Dummies (11)	No	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Relative RMSE	1	1.07	0.38	0.38	0.41	0.39	0.43	0.38

Note: Standard errors in brackets

*Denote statistical significance at the 10% level **Denote statistical significance at the 5% level ***Denote statistical significance at the 1% level criterion of the model strongly increases if we add a dynamic component to the migration equation. The relative RSME for each estimator is thereby computed as the ratio of the model's RMSE and the static POLS benchmark specification in column 1. A value smaller than one indicates that the model has a better predictive performance than the benchmark POLS.

As discussed above the λ-class estimators are potentially biased in a dynamic specification. Since the coefficient of the lagged dependent variable turns out to be highly significant, we also compute a bias-corrected FEM specification as well as the Arellano and Bond (1991) and Blundell and Bond (1998) system GMM estimators. According to the relative RMSE criterion the Blundell–Bond system GMM specification has the smallest prediction error. The coefficients for labor market signals are statistically significant and of the expected signs. Moreover, the SYS-GMM specification passes standard tests for autocorrelation in the residuals (m_1 and m_2 statistics proposed by Arellano and Bond 1991) as well as the Hansen J-statistic for instrument validity. The reported C-statistic for the exogeneity of the instruments in the level equation shows the validity of the augmented approach in extension to the standard Arellano–Bond first difference model.

We then use the SYS-GMM approach to test for the significance of different extensions of the baseline Harris–Todaro model. We start by including a dummy variable for the East German Spatial Planning Regions (see Table 3.6). The motivation for this approach is to test for the significance of the so-called East German empirical puzzle, where a relatively high degree of migratory interregional immobility was found to coexist with large regional labor market disparities. Fachin (2007) and Etzo (2007) report similar results for Italian South–North migration trends, while Alecke and Untiedt (2000) as well as Alecke et al. (2010) identify such effects for German East–West migration throughout the 1990s.[10]

The results in Table 3.6 for the period 1996 to 2006 report a statistically significant positive East German dummy that indicates higher net in-migration balances for the East German Spatial Planning Regions than their labor market performance would suggest. To obtain further insights we also estimate a specification that includes federal state level fixed effects. The estimation results for the state dummies in the baseline model are shown in Fig. 3.3.[11] As the figure highlights, for all six East German state dummies we obtain statistically significant and positive coefficients. Negative coefficients are found for the West German states Baden Württemberg, Bavaria and Hessen. A Wald test for the joint effect of the set of state dummies turns out to be highly significant. However, most importantly, for both models including the East German dummy and the set of state dummies, the impact of labor market variables is still of the expected sign and higher than in the baseline specification. In line with Suedekum (2004) for West Germany, the results thus show

[10]The latter study found that along with a second wave of East–West movements in early 2000 net flows out of East Germany were much higher than expected after controlling for its labor market and macroeconomic performance. Since this trend was accompanied by a gradual fading out of economic distortions, this supports the view of 'repressed' migration flows for that period.

[11]Detailed regression results for the state dummies are reported in Table 3.8 in Appendix A.

Table 3.6 Augmented neoclassical migration model for German spatial planning regions

$nm_{ij,t}$	SYS-GMM					
$nm_{ij,t-1}$	0.87***	0.87***	0.89***	0.87***	0.86***	0.89***
	(0.001)	(0.001)	(0.001)	(0.002)	(0.002)	(0.003)
$\tilde{u}_{ij,t-1}$	−0.33***	−0.52***	−0.25***	−0.58***	−0.86***	−0.86***
	(0.008)	(0.022)	(0.030)	(0.034)	(0.060)	(0.058)
$\tilde{y}_{ij,t-1}$	0.47***	0.48***	0.30***	1.25***	0.84***	1.05***
	(0.046)	(0.11)	(0.047)	(0.118)	(0.172)	(0.225)
EAST	0.29***			0.63***		
	(0.016)			(0.045)		
COMM			−0.02***	−0.02***	−0.05***	−0.05***
			(0.002)	(0.002)	(0.006)	(0.007)
HK						0.004
						(0.011)
INTCOMP						0.05**
						(0.021)
	Type of settlement structure					
Type 2				−0.07**	−0.53***	−0.40***
				(0.035)	(0.143)	(0.126)
Type 3				0.01	−0.10	−0.02
				(0.039)	(0.083)	(0.088)
Type 4				−0.12***	−0.24***	−0.16*
				(0.041)	(0.085)	(0.082)
Type 5				0.02	−0.12	−0.01
				(0.049)	(0.088)	(0.095)
Type 6				−0.05	−0.08	0.04
				(0.047)	(0.094)	(0.107)
Type 7				−0.05	−0.29***	−0.15
				(0.045)	(0.110)	(0.117)
No. of obs.	1067	1067	873	873	873	753
Time dummies (11)	167.9***	12.4***	32.3***	12.8***	16.5***	6.4***
State dummies (16)	No	21.7***	No	No	26.6***	27.8***
m_1	(0.38)	(0.37)	(0.50)	(0.57)	(0.55)	(0.64)
m_2	(0.24)	(0.24)	(0.21)	(0.20)	(0.20)	(0.20)
J-stat. overall	(0.52)	(0.67)	(0.16)	(0.12)	(0.31)	(0.22)
C-stat. LEV-EQ	(0.99)	(0.99)	(0.76)	(0.63)	(0.97)	(0.57)
C-stat. exog. var.	(0.07)	(0.99)	(0.00)	(0.00)	(0.33)	(0.11)
C-stat. CD-GMM	–	(0.58)	–	–	(0.35)	(0.57)

Note: In the regressions including the regional settlement structure the dummy for highly agglomerated areas of Type 1 is excluded and thus serves as the benchmark category for the further settlement type dummies. Standard Errors in brackets. For m_1, m_2, J- and C-statistic test results p-values are reported

*Denote statistical significance at the 10% level **Denote statistical significance at the 5% level

***Denote statistical significance at the 1% level

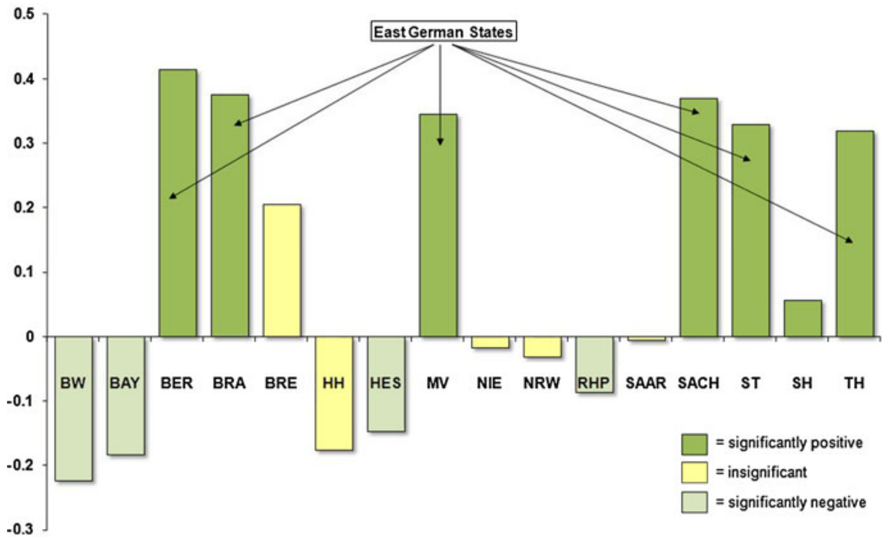

Fig. 3.3 State level effects for German states in the aggregate baseline migration model. *Note*: Computations based on Table 3.5

that macro regional differences matter, yet there are no qualitative effects on the estimated coefficients that hint to a systematic rejection of the neoclassical migration model.

Regarding further regressors in the augmented variable set, the results show that higher interregional net in-commuting levels are negatively correlated with the net in-migration rate. This supports our basic theoretical expectations from above that both types are alternative adjustment mechanisms to reduce labor market disparities. The binary dummy variables for different settlement types (classified by size of local urban centers and population density, see Table 3.1 for details) reveal further structural differences in inter-regional migration patterns. Next to rural areas with low population density, agglomeration regions of Types 2 and 4 also show significantly lower net in-migration rates relative to benchmark category Type 1 (highly agglomerated area with a regional urban center above 100,000 persons and population density above 300 inhabitants/sqm). This may hint at the role played by regional centers of agglomeration in attracting migration flows and may be interpreted in favor of a 're-urbanization' process in Germany for the period 1996 to 2006. Similar trends have also been reported by Swiaczny et al. (2008).[12]

Finally, testing for the effects of regional human capital endowments and international competitiveness shows mixed results. While the proxy for the latter variable in terms of foreign turnover relative to total turnover in manufacturing sector industries shows the expected positive effect on net in-migration, the regional endowment

[12]The authors argue that throughout the process of demographic change in Germany city core regions may gain in demographic terms from young migrants, while suburban and rural areas are expected to face increasing migration losses.

with human capital is found to be insignificant. This finding corresponds to recent results for Spain between 1995–2002, where regional differences in human capital were not found to be helpful in predicting internal migration flows (see Maza and Villaverde 2004). The latter may be explained by the fact that not the region's specific stock of human capital but rather the individual endowment of the prospective migrant is the appropriate level of measurement. However, the latter variable is not observable for regional data.

In order to check the appropriateness of our augmented SYS-GMM specifications, we perform a variety of postestimation tests for instrument appropriateness, as well as temporal and cross-sectional dependence of the error term. The test results are reported in Table 3.6. With respect to IV appropriateness and temporal autocorrelation of the error terms, all model specifications show satisfactory results. In order to control for cross-sectional error dependence due to unobserved common factors, we first add year dummies to our model specification, which also turn out to be jointly significant. We then apply Sargan's difference test for the SYS-GMM model ($C_{CD\text{-}GMM}$) as described above, in order to check for the nature of the cross-sectional dependence given the impact of unobserved common factors.

In order to run the test, we first need to judge whether the set of explanatory variables (excluding instruments for the lagged endogenous variable) is exogenous with respect to the combined error term. This can easily be tested by means of a Sargan/Hansen J-statistic based overidentification test. As the results in Table 3.6 show, only those model specification that include fixed state effects pass the overidentification test for the vector of explanatory variables. For these equations we can then apply $C_{CD\text{-}GMM}$ from (3.13) in order to test for the existence of heterogeneous factor loadings for the common factor structure of the error terms as proposed by Sarafidis et al. (2009). The test results do not indicate any sign of misspecification when including period-fixed effects for standard significance levels, hinting at homogeneous responses to common shocks. In sum, the augmented neoclassical migration equation is shown to be an appropriate representation of the data generating process and highlights the role of key labor market variables in explaining net in-migration rates for German regions.

3.6.2 Disaggregate Estimates by Age Groups

Given the supportive findings for the neoclassical migration model at the aggregate level, we finally aim to check the sensitivity of the results when different disaggregated age groups are used. We are especially interested in analyzing whether the estimated coefficients for the labor market signals change for different age-groups. Indeed, the estimation results show that the migratory response to labor market variables is much higher for workforce relevant age groups. For both the baseline and augmented model, the resulting coefficients for real income and unemployment rate differences together with 95% confidence intervals are plotted in Fig. 3.4.[13]

[13]Detailed estimation results for the models are given in Appendix B.

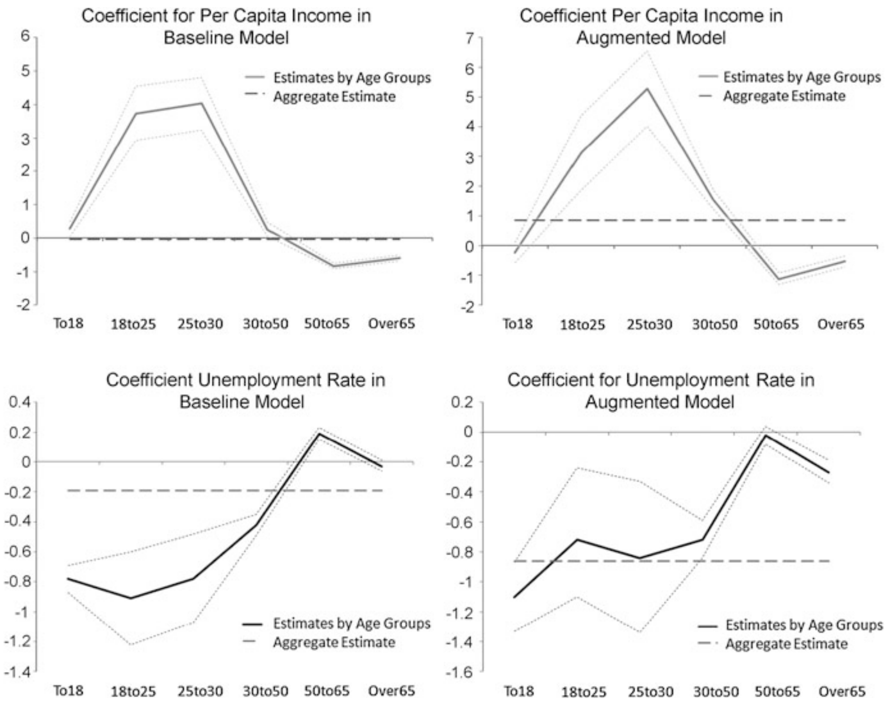

Fig. 3.4 Coefficients for income ($\tilde{y}_{ij,t-1}$) and unemployment rate differences ($\tilde{u}_{ij,t-1}$) by age groups. *Source*: Dotted lines denote 95% confidence intervals

The coefficient for real income differences in Fig. 3.4 shows a clear inverted U-shaped pattern when plotted for the different age-groups in ascending order. While for migrants aged up to 18 years real income differences do not seem to matter, for migrants aged between 18 to 25 and 25 to 30 years the estimated coefficient is statistically significant and much higher compared to the overall migration equation reported in Table 3.6. For older age-groups the effect reduces gradually. The migration responses are found to be very similar for the baseline and augmented migration specification (see Fig. 3.4). Similar results were found for regional unemployment rate differences, which are shown to be almost equally important for age groups up to 50 years. It is only for elderly age groups that the coefficients turn out to be of smaller size and partly insignificant. If we look at the distribution of the state-level fixed effects for each estimated age-group specification, the estimation results show that the positive dummy variable coefficients for the East German states particularly hold for the workforce relevant age groups. The results are graphically shown in Fig. 3.5 for the baseline migration model.

Finally, Table 3.7 computes the 'relative importance' of the labor market variables by age-groups in determining net migration flows. Thereby, the relative importance refers to the quantification of an individual regressor's contribution in a multiple regression model (see e.g. Grömping 2006, for an overview). This allows us to further answer the question as to how far our estimation results support the

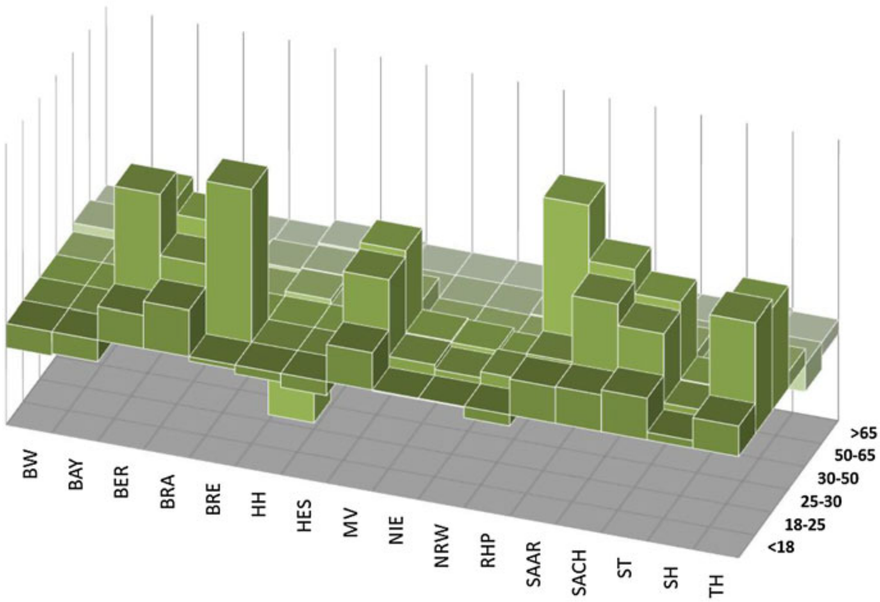

Fig. 3.5 State level effects in baseline migration model by states and age. *Note*: For details of calculation see Tables 3.9 and 3.10

Table 3.7 Relative contribution of labor market variables in explaining migration flows

Age-group	Specification A			Specification B		
	$y_{ij,t-1}$	$u_{ij,t-1}$	Joint	$y_{ij,t-1}$	$u_{ij,t-1}$	Joint
Up to 18	1%	3%	4%	0%	19%	19%
18 to 25	29%	21%	50%	19%	8%	27%
25 to 30	18%	14%	31%	54%	11%	65%
30 to 50	1%	5%	6%	5%	8%	13%
50 to 65	1%	1%	1%	2%	0%	2%
Over 65	1%	0%	2%	1%	1%	2%

Note: Specification A is based on the computation of the squared correlation of the respective regressor with the dependent variables (univariate R^2). Specification B is calculated using the estimated SYS-GMM coefficient from the augmented migration model specification in Table 3.10 (see Appendix B). The estimation coefficient for regressor x_k is further standardized as $\hat{\beta}_{standardized,k} = \hat{\beta}_k \frac{\sqrt{s_{kk}}}{\sqrt{s_{yy}}}$, where s_{kk} and s_{yy} denote the empirical variances of regressor x_k and the dependent variable y, respectively. As long as one only compares regressors within models for the same y, division by $\sqrt{s_{yy}}$ is irrelevant

prominent role of labor market conditions in guiding internal migration rates (of the workforce population) in Germany. Table 3.7 computes two specifications based on the squared correlation of the respective regressor with the dependent variables (univariate R^2, specification A) as well as the standardized estimated SYS-GMM coefficients from the augmented migration model. This latter metric for assessing the relative importance of regressors has an advantage over the simple benchmark in specification A since it accounts for the correlation of regressors. As the table shows, both methods assign a significant explanatory share to the two key labor market variables in predicting migration flows, especially for the workforce population (up to 50% joint contribution in Specification A for the age-group 18 to 25 years and even up to 65% for the age-group 25 to 30 years in Specification B). The SYS-GMM thereby on average assigns a stronger weight to real income differences in explaining net in-migration relative to unemployment differences. However, the overall picture confirms our interpretation of the regression tables in assigning a prominent role to labor market imbalances in driving German internal migration.

3.7 Conclusion

In this paper, we have analyzed the explanatory power of the neoclassical migration model to describe aggregate and age-group specific internal migration trends for 97 German Spatial Planning regions throughout the period 1996–2006. Our results are based on model specifications for dynamic panel data estimators and give strong evidence in favor of the neoclassical inspired Harris–Todaro model. Both real income differences as well as unemployment rate disparities are found to be statistically significant with the expected signs. That is, a real income increase in region i relative to region j leads to higher net migration inflows to i from j; on the contrary, a rise in the regional unemployment rate in i leads to lower net inflows. Given these responses to labor market signals, migration flows may be seen as a spatial adjustment mechanism and equilibrate regional labor market imbalances.

The results of the standard neoclassical migration model remain stable if commuting flows, regional human capital endowment, the region's international competitiveness as well as differences in the settlement structure are added as further explanatory variables. The inclusion of the regional net in-commuting rate shows a negative correlation with migration underlying the substitutive nature of the two variables. Also, an increasing level of international competitiveness attracts further in-migration flows. We also find heterogeneity for different types of regional settlement structure proxied by population density and we observe persistent structural differences for the two East–West macro regions (by including individual federal state level fixed effects or a combined East German dummy). Most importantly, the impact of core labor market variables is still of the expected sign, when further variables are added. In line with earlier empirical studies, the results thus show that macro regional differences matter, yet there are no qualitative effects on the estimated coefficients that hint to a systematic rejection of the neoclassical migration model.

We finally estimate the migration model for age-group specific subsamples of the data. Here, the impact of labor market signals is found to be of greatest magnitude for workforce relevant age groups (18 to 25, 25 to 30 and 30 to 50 years). Computing the 'relative importance' of labor market variables by age groups in a multiple regression framework with a broader set of controls, our results show that for young cohorts up to 65% of all migratory movements can be explained by differences in regional income levels and unemployment rates. This latter result emphasizes the prominent role played by labor market conditions in guiding internal migration rates of the working age population in Germany.

Appendix A: Estimated State Level Effects in Migration Models

Table 3.8 State level effects in baseline and augmented migration model

Model	Baseline	Augmented
BW	−0.22***	−0.27***
	(0.023)	(0.079)
BAY	−0.18***	−0.39***
	(0.019)	(0.119)
BER	0.42**	1.12***
	(0.188)	(0.264)
BRA	0.38***	0.63***
	(0.045)	(0.137)
BRE	0.20	1.23**
	(0.255)	(0.492)
HH	−0.18	1.08*
	(0.346)	(0.553)
HES	−0.15***	−0.32**
	(0.030)	(0.125)
MV	0.34***	0.53***
	(0.045)	(0.125)
NIE	−0.02	−0.05
	(0.021)	(0.105)
NRW	−0.03	0.02
	(0.026)	(0.059)
RHP	−0.09***	−0.67***
	(0.023)	(0.129)
SAAR	−0.01	−0.49
	(0.254)	(0.583)
SACH	0.37***	0.79***
	(0.052)	(0.174)
ST	0.33***	0.23*
	(0.047)	(0.133)
SH	0.06**	0.07
	(0.024)	(0.107)
TH	0.32***	0.19
	(0.037)	(0.154)

Note: BW = Baden-Württemberg, BAY = Bavaria, BER = Berlin, BRA = Brandenburg, BRE = Bremen, HH = Hamburg, HES = Hessen, MV = Mecklenburg-Vorpommern, NIE = Lower Saxony, NRW = North Rhine-Westphalia, RHP = Rhineland-Palatine, SAAR = Saarland, SACH = Saxony, ST = Saxony-Anhalt, SH = Schleswig-Holstein, TH = Thuringia. Baseline results according to the SYS-GMM specification in Table 3.5, augmented model results according to column 5 in Table 3.6

*Denote statistical significance at the 10% level

**Denote statistical significance at the 5% level

***Denote statistical significance at the 1% level

Appendix B: Baseline and Augmented Regression Results by Age Groups

Table 3.9 Baseline migration model based on system GMM estimation

$nm_{ij,t}$	To 18	18 to 25	25 to 30	30 to 50	50 to 65	Over 65
$nm_{ij,t-1}$	0.87***	0.86***	0.86***	0.87***	0.90***	0.88***
	(0.001)	(0.005)	(0.004)	(0.002)	(0.001)	(0.002)
$\tilde{u}_{ij,t-1}$	−0.78***	−0.91***	−0.78***	−0.42***	0.19***	−0.03
	(0.044)	(0.156)	(0.148)	(0.036)	(0.019)	(0.018)
$\tilde{y}_{ij,t-1}$	0.28**	3.73***	4.03***	0.25**	−0.83***	−0.59***
	(0.112)	(0.406)	(0.395)	(0.102)	(0.042)	(0.043)
BW	−0.31***	−0.35***	−0.37***	−0.17***	0.11***	0.01
	(0.035)	(0.093)	(0.093)	(0.018)	(0.016)	(0.011)
BAY	−0.28***	−0.21***	−0.20***	−0.15***	0.07***	−0.01
	(0.031)	(0.075)	(0.077)	(0.018)	(0.016)	(0.009)
BER	0.42***	1.67**	1.32	0.12	−0.17***	−0.02
	(0.144)	(0.721)	(0.937)	(0.187)	(0.054)	(0.068)
BRA	0.59***	0.89***	1.12***	0.36***	−0.24***	−0.06***
	(0.044)	(0.171)	(0.156)	(0.052)	(0.019)	(0.018)
BRE	−0.06	1.95***	−0.38	−0.03	0.04	−0.10***
	(0.256)	(0.610)	(0.470)	(0.161)	(0.107)	(0.133)
HH	−0.11	−0.12	−1.22	−0.12	0.07	0.09
	(0.410)	(0.712)	(1.133)	(0.018)	(0.125)	(0.160)
HES	−0.18***	−0.22*	−0.27**	−0.12***	0.09***	0.03
	(0.045))	(0.133)	(0.110)	(0.018)	(0.031)	(0.027)
MV	0.48***	1.11***	1.19***	0.26***	−0.31***	−0.12***
	(0.047)	(0.171)	(0.164)	(0.051)	(0.022)	(0.021)
NIE	−0.01	0.14**	0.15**	−0.02	−0.05***	−0.04***
	(0.020)	(0.065)	(0.057)	(0.017)	(0.011)	(0.007)
NRW	−0.01	0.08	0.13*	−0.02	−0.01	−0.01
	(0.035)	(0.065)	(0.071)	(0.019)	(0.010)	(0.008)
RHP	−0.14***	0.15	0.08	−0.08***	0.02	−0.04***
	(0.035)	(0.102)	(0.089)	(0.017)	(0.026)	(0.014)
SAAR	0.46	0.49	2.20**	0.07	0.11	0.03
	(0.384)	(0.764)	(1.062)	(0.153)	(0.176)	(0.082)
SACH	0.47***	1.33***	1.49***	0.24***	−0.33***	−0.15***
	(0.055)	(0.194)	(0.177)	(0.052)	(0.028)	(0.022)
ST	0.53***	1.06***	1.17***	0.25***	−0.35***	−0.15***
	(0.088)	(0.177)	(0.178)	(0.051)	(0.020)	(0.021)
SH	0.10***	0.18*	0.19***	0.07***	0.07***	0.03
	(0.030)	(0.094)	(0.056)	(0.013)	(0.013)	(0.007)
TH	0.39***	1.42***	1.31***	0.21***	−0.34***	−0.18***
	(0.058)	(0.212)	(0.173)	(0.048)	(0.019)	(0.018)
No. of obs.	1067	1067	1067	1067	1067	1067
Time dummies (11)	Yes	Yes	Yes	Yes	Yes	Yes

Note: BW = Baden-Württemberg, BAY = Bavaria, BER = Berlin, BRA = Brandenburg, BRE = Bremen, HH = Hamburg, HES = Hessen, MV = Mecklenburg-Vorpommern, NIE = Lower Saxony, NRW = North Rhine-Westphalia, RHP = Rhineland-Palatine, SAAR = Saarland, SACH = Saxony, ST = Saxony-Anhalt, SH = Schleswig-Holstein, TH = Thuringia
*Denote statistical significance at the 10% level **Denote statistical significance at the 5% level
***Denote statistical significance at the 1% level

Table 3.10 Augmented migration model based on system GMM estimation

$nm_{ij,t}$	To 18	18 to 25	25 to 30	30 to 50	50 to 65	Over 65
$nm_{ij,t-1}$	0.86***	0.85***	0.87***	0.87***	0.90***	0.84***
	(0.002)	(0.006)	(0.006)	(0.003)	(0.002)	(0.003)
$\tilde{u}_{ij,t-1}$	−1.10***	−0.72***	−0.84***	−0.72***	−0.02	−0.27***
	(0.117)	(0.239)	(0.256)	(0.061)	(0.032)	(0.035)
$\tilde{y}_{ij,t-1}$	−0.23	3.13***	5.28***	1.55***	−1.12***	−0.53***
	(0.175)	(0.633)	(0.369)	(0.157)	(0.097)	(0.090)
COMM	−0.10***	−0.06***	−0.04**	−0.01**	−0.02***	−0.03***
	(0.010)	(0.014)	(0.015)	(0.005)	(0.002)	(0.003)
BW	−0.19	−0.28	−0.85***	−0.39***	0.14***	−0.02
	(0.136)	(0.229)	(0.179)	(0.068)	(0.046)	(0.037)
BAY	−0.59***	−0.37	−0.98***	−0.39***	0.05	−0.11**
	(0.193)	(0.261)	(0.237)	(0.077)	(0.056)	(0.052)
BER	1.41***	1.02	0.81	0.59**	0.02	0.49***
	(0.481)	(1.182)	(1.157)	(0.279)	(0.136)	(0.186)
BRA	0.59***	0.37	065*	0.71***	−0.18***	0.04
	(0.164)	(0.365)	(0.350)	(0.103)	(0.046)	(0.055)
BRE	1.95**	2.76	−1.37	0.24	0.08	0.39
	(0.782)	(2.015)	(0.934)	(0.458)	(0.211)	(0.435)
HH	1.00	1.07	−1.23*	−0.41	0.35	0.09
	(1.173)	(1.183)	(0.629)	(0.424)	(0.368)	(0.611)
HES	−0.18	−0.33	−0.86***	−0.39***	0.13**	0.01
	(0.209)	(0.248)	(0.198)	(0.072)	(0.058)	(0.057)
MV	0.26*	0.41	0.76**	0.63***	−0.16***	−0.02
	(0.133)	(0.288)	(0.312)	(0.084)	(0.048)	(0.059)
NIE	−0.26*	−0.17	−0.52**	−0.06	0.05	−0.08**
	(0.139)	(0.264)	(0.198)	(0.083)	(0.047)	(0.033)
NRW	0.06	0.09	−0.12	−0.05	0.03	0.01
	(0.076)	(0.183)	(0.157)	(0.056)	(0.032)	(0.028)
RHP	−1.31***	−0.71***	−0.91***	−0.32***	−0.09*	−0.38***
	(0.226)	(0.247)	(0.286)	(0.089)	(0.051)	(0.066)
SAAR	−0.11	0.17	0.86	−0.33	0.26	0.06
	(0.736)	(1.279)	(1.361)	(0.488)	(0.249)	(0.227)
SACH	0.57***	0.96**	1.21***	0.75***	−0.34***	−0.08
	(0.188)	(0.405)	(0.403)	(0.115)	(0.061)	(0.066)
ST	−0.23	0.13	0.54	0.56***	−0.31***	−0.23***
	(0.176)	(0.321)	(0.352)	(0.088)	(0.048)	(0.055)
SH	0.11	−0.22	−0.56***	−0.02	0.09**	0.06
	(0.165)	(0.266)	(0.211)	(0.089)	(0.046)	(0.043)
TH	−0.45*	0.46	0.77**	0.53***	−0.34***	−0.18*
	(0.256)	(0.306)	(0.360)	(0.102)	(0.067)	(0.102)
No. of obs.	873	873	873	873	873	873
Time dummies (11)	Yes	Yes	Yes	Yes	Yes	Yes
Settlement type (6)	Yes	Yes	Yes	Yes	Yes	Yes

Note: BW = Baden-Württemberg, BAY = Bavaria, BER = Berlin, BRA = Brandenburg, BRE = Bremen, HH = Hamburg, HES = Hessen, MV = Mecklenburg-Vorpommern, NIE = Lower Saxony, NRW = North Rhine-Westphalia, RHP = Rhineland-Palatine, SAAR = Saarland, SACH = Saxony, ST = Saxony-Anhalt, SH = Schleswig-Holstein, TH = Thuringia

*Denote statistical significance at the 10% level **Denote statistical significance at the 5% level

***Denote statistical significance at the 1% level

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Chapter 4
Space–Time Dependence in Internal Migration Flows: Evidence for Germany since Re-unification

4.1 Introduction

This paper aims to take an explicit account of spatial interdependencies in dynamic panel data (DPD) models to explain German internal migration flows since re-unification. While general research in the field of spatial econometrics has evolved rapidly within the last years (see Florax and Van der Vlist 2003; Anselin 2007; Elhorst 2010), spatial applications to time dynamic panel data models are still at an experimental stage. Nevertheless, a proper handling of spatial autocorrelation besides controlling for time dynamic adjustment processes may have important implications from a statistical as well as theoretical perspective.[1] Regarding the latter point, different scholars have already pointed out the likely role played by spatial autocorrelation in analyzing migration (see e.g. Cushing and Poot 2003, and LeSage and Pace 2008, 2009). Spatial autocorrelation measures the correlation of values for an individual variable, which are strictly attributable to the proximity of those values in geographic space. Depending on its source, spatial interdependences may either be captured through a spatial lag term of the dependent variable, the explanatory variables and/or the error term. In this paper we take a general perspective and apply both the spatial lag as well as the unconstrained spatial Durbin model, which augments the spatial lag approach by additionally controlling for spatially lagged terms of the exogenous variables.

Given the experimental stage of DPD models with spatial effects, next to the empirical focus of this chapter, our proposed research design also faces several methodological challenges which will be tackled in the following. To do so, we use an estimation strategy that starts from the standard Blundell–Bond (1998) system GMM approach (SYS-GMM) and augments the latter estimator by valid instruments for the spatial lag variables. For model validation purposes we conduct a battery of residual testing to account for instrument relevance and consistency, as well as check for remaining residual autocorrelation. The main advantage of our es-

[1]The importance of timely adjustment processes in modelling internal migration flows for Germany has already been shown in Chap. 2.

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timation approach is that it stays within the flexible SYS-GMM framework (which is now available for many econometric software packages) combined with an explicit treatment of spatial issues and a flexible tool for handling potential endogeneity issues among the set of regressors. Using a Monte Carlo simulation exercise, Kukenova and Monteiro (2008) have recently shown that the spatially augmented SYS-GMM can consistently estimate the spatially augmented specifications for standard data settings (large N, small T). First applications of the spatial dynamic panel model estimated by GMM are given in Bouayad-Agha and Vedrine (2010) as well as Elhorst et al. (2010). The latter authors also show how to effectively combine the GMM approach with alternative (ML based) estimation techniques in order to increase the estimator's overall performance.

Of vital importance in the context of migration flow modelling is the appropriate specification of a spatial weighting scheme for identifying the underlying spatial autocorrelation structures and interpreting the obtained regression results in the light of theory (see Black 1992). We will put a special focus on the specification of spatial weighting matrices for internal migration flow data. We then use the derived spatial variables for a space–time analysis of German migration dynamics. Besides testing for the significance of space–time adjustment processes, a particular interest is to analyze whether the effect of regional labor market signals also hold for spatially upgraded versions. The latter variables are typically found to be an important driving force of internal migration flows in the standard (aspatial) empirical literature. Moreover, given the novelty of econometric tools for the joint handling of space–time dynamic processes, the paper also tries to explore, how to consistently and efficiently estimate these rather complex relationships.

The remainder of the paper is organized as follows: In the next section, we outline our empirical estimation strategy, starting from a short description of the neoclassical migration model. We then discuss different methods for spatial upgrading dynamic panel data estimators and demonstrate how network dependency structures can be translated into a spatial weighting matrix for empirical estimation. After a brief overview of the data used for estimation purposes and a exploratory space–time data analysis of migration flows between German states in Sect. 4.3, Sect. 4.4 estimates the different spatial dynamic panel models by means of SYS-GMM. We include spatial lag and spatial Durbin model specifications as well as standard SYS-GMM to spatially filtered variable as a benchmark case. Since our results reveal pros and cons of the different estimation methods, we finally also report the performance of mixed spatial filtering-regression techniques as a solution to estimation settings with (many) endogenous regressors. Section 4.5 gives a conclusion and outlook for further research questions.

4.2 Econometric Model Specification

4.2.1 Neoclassical Migration: A Benchmark Model

In this section we briefly outline the neoclassical migration model as a starting point for our empirical analysis. According to the neoclassical framework, a representative agent decides to move between two regions if this improves his welfare position relative to not moving. Relevant factors for this decision are the expected incomes in the home (origin) and alternative (destination) region net of ‘transportation’ costs for the case of moving. Expected income in turn can be expressed a function of the (real) wage rate and the probability of being employed, where the latter is inversely related to the regional unemployment rate. This underlying idea has been formally elaborated by Harris and Todaro (1970) and can be summarized in terms of a stylized equation for net in-migration $nm_{ij,t}$ between region i and region j in time period t (with variables in logarithms) as

$$\begin{aligned} nm_{ij,t} = {} & \alpha nm_{ij,t-1} + \beta_1 \widetilde{wr}_{ij,t-1} + \beta_2 \widetilde{ur}_{ij,t-1} + \beta_3 \Delta \widetilde{ylr}_{ij,t-1} \\ & + \beta_4 \tilde{q}_{ij,t-1} + \beta_5 \widetilde{hc}_{ij,t-1} + \beta_6 \Delta \widetilde{p}^{l}_{ij,t-1} + \mu_{ij} + \nu_{ij,t}. \end{aligned} \tag{4.1}$$

To keep the number of estimation parameter at a minimum, we restrict explanatory variables to enter as inter-regional differences resulting in a triple-indexed model specification, where $\tilde{x}_{ij,t}$ for any variable $x_{ij,t}$ is defined as $\tilde{x}_{ij,t} = (x_{i,t} - x_{j,t})$. The error term is assumed to have the typical one-way error component structure $(\mu_{ij} + \nu_{ij,t})$. We define net migration as the ratio of in- and out-migration for each period so that we can write it in logs as $nm_{ij,t} = (inm_{ij,t} - outm_{ij,t})$. Next to the core labor market variables in terms of real wages $(\widetilde{wr})$ and unemployment rates $(\widetilde{ur})$, we include growth in real labor productivity $(\Delta\widetilde{ylr})$, the labor participation rate $(\tilde{q})$, a human capital index $(\widetilde{hc})$ and the annual growth in land prices $(\Delta\widetilde{p}^l)$ as control variables. To account for differences in the standards of living, we explicitly deflate real wages by regional consumer prices (see e.g. Roos 2006, for details).

According to the neoclassical migration model we expect that a (relative) increase in the home region’s real wage rate *ceteris paribus* leads to higher net inflows, while a (relative) real wage rate increase in region j results in lower net in-migration flows to region i. By contrast, an increase in the unemployment rate in region i relative to j has negative effects on net in-migration to i. Costs of moving between the two regions are typically expected to be an impediment to migration and are thus supposed to be negatively correlated with net migration. In addition to these economic factors in the stylized migration equation, we also account for likely information lags in the transmission process from the explanatory to the endogenous variable, and thus assume that migration flows themselves adjust with a lag structure. The inclusion of the time lagged endogenous variable has proven to be an important factor in the adjustment path of German migration flows (see e.g. Alecke et al. 2010) and may reflect different channels through which past flows affect current migration (e.g. since migrants serve as communication links for friends and relatives left behind). These linkages in turn may have a potential impact on prospective migrants who want to live in an area where they share cultural and social backgrounds with other residents (see e.g. Chun 1996, as well as Rainer and Siedler 2009, for a detailed discussion). Moreover, the existence of such social networks may not only determine the time adjustment path of migration flows but also affect their spatial distribution. We come to this point in the following.

4.2.2 Spatial Upgrading of Dynamic Panel Data Models

In most empirical work, migration flows between an origin and a destination region have been typically assumed to be independent of other migration flows associated with different origin destination pairs. However, as Chun (2008) points out, each individual migration decision may be seen as the result of choice processes in space, which is likely to be influenced by other migration flows at the macro level. In this sense, outflows from a particular origin may be correlated with other outflows that have the same origin and geographically proximate destination regions given unobservable characteristics of origins and destinations in the sample. The associated dependency among flow data is measured in terms of network autocorrelation. If empirical model building does not account for such network autocorrelation effects in mapping migration flows, results are likely to be biased and may lead to unreliable conclusions (see e.g. LeSage and Pace 2008). Thus, in a fairly general modelling framework, both space and time lags should be considered in order to minimize the risk of spurious regression results.

Given the likely importance of interdependences in migration flows across time and space, in this section we propose an estimation strategy, which is able to account for spatial dependence in a dynamic panel data model using the above designed spatial weighting scheme. As Bouayad-Agha and Vedrine (2010) point out, estimation methods for the simultaneous treatment of space and time interrelations must deal with three main and potentially interlinked problems: First, there may be serial dependence at each point in time; second, spatial dependence at each point of time may also be present; and finally, there may be additional unobservable effects specific to space and time periods. To account for the problems, recently different approaches to deal with these problems have been designed: Elhorst (2005) proposes a maximum likelihood estimator (MLE) for spatial lag panel models, Lee and Yu (2010) as well as Yu et al. (2008) study asymptotic quasi-maximum likelihood estimator (QMLE) properties. Fixed-effect type IV based methods are applied for instance in Beenstock and Felsenstein (2007) as well as Korniotis (2010).

Alternatively, building upon recent advances in using GMM methods for DPD processes, Bouayad-Agha and Vedrine (2010) as well as Kukenova and Monteiro (2008) suggest extensions to the Arellano–Bond (1991) and Blundell–Bond (1998) GMM estimators by additional moment conditions for the spatially lagged variables. The GMM approach has the advantage that it can easily deal with any type of right hand side endogeneity in terms of correlation of regressors with the composed error term. Using Monte Carlo simulations, Kukenova and Monteiro (2008) have shown that in the presence of endogenous covariates, the bias of the spatial lag (ρ) remains relatively low for GMM estimators, while the endogeneity bias arising from correlated regressors may grow large, if it is not corrected. In this setup, the SYS-GMM estimator clearly performs best.

Our empirical modelling strategy based on SYS-GMM starts from a fairly general space–time augmented specification, which accounts jointly for time lags, spatial lags and time-spatial lags of the endogenous and exogenous variables as

$$
\begin{aligned}
y_{i,t} = \alpha y_{i,t-1} + \rho \sum_{j \neq i} w_{ij} \times y_{j,t} + \phi \sum_{j \neq i} w_{ij} \times y_{j,t-1} \\
+ \sum_{m=0} \beta_m x_{i,t-m} + \sum_{m=0} \gamma_m \sum_{j \neq i} w_{ij} \times x_{j,t-m} + \mu_i + \nu_{i,t} \\
\text{with } \nu_{i,t} = \lambda \sum_{i \neq j} w_{ij} \times \nu_{i,t} + \nu_{i,t},
\end{aligned}
\tag{4.2}
$$

where the endogenous $y_{i,t}$ and exogenous variables $x_{i,t}$ vary in the cross-sectional dimension with $i = 1, \ldots, N$ and the time series dimension with $t = 1, \ldots, T$, $w_{i,j}$ are elements of a spatial weight matrix W, where j denotes observations in the neighborhood of i. Note that—for notational convenience—we use the standard double indexed (or 'entity'-based) classification here. The extension to the case of dyadic or flow data is nevertheless rather straightforward, e.g. we can simply define i as a pair of origin destination flows ij. We return to the triple indexed notation according to (4.1) at a later stage of the analysis.

The model contains two error components, namely a time-fixed unobservable effect μ_i for each cross-section unit and a time-varying error term $\nu_{i,t}$. The parameter ρ, ϕ, γ_m and λ measure the degree of spatial dependence in the model. Given that (4.2) is a combination of a time and spatial autoregressive model, we need to ensure that the resulting process is stationary. The stationarity restrictions in this model are stronger than the individual restrictions imposed on the coefficients of a pure spatial or time dynamic model. Here, covariance stationarity requires that the summation of the time autoregressive parameter α and the spatial lag coefficients ρ and ω satisfies the following condition:

$$
|\alpha| < 1 - (\rho + \phi)\lambda_{\max} \quad \text{if } \rho, \phi \geq 0, \tag{4.3}
$$

$$
|\alpha| < 1 - (\rho + \phi)\lambda_{\min} \quad \text{if } \rho, \phi < 0, \tag{4.4}
$$

where $\lambda_{\min}$ and $\lambda_{\max}$ are the smallest and highest eigenvalues of the spatial weight matrix W, with $\lambda_{\min} < 0 < \lambda_{\max}$. The spatial effects are then assumed to lie between $\frac{1}{\lambda_{\min}}$ and $\frac{1}{\lambda_{\max}}$.[2]

By adding restrictions to the parameters of the model, we can derive commonly known spatial model specifications with additional time dynamics such as the

- spatial Durbin model (SDM) with $\lambda = 0$ and
- spatial Durbin error model (SDEM) with $\rho = 0$ and $\phi = 0$.

The difference between the two specifications is that besides spatial lags of the exogenous variables the SDEM allows only for spatial dependency in the error term $\nu_{i,t}$, while the SDM includes spatial lags of the dependent variable as well. In both model specifications, the spatial structure measured by ρ, ϕ and λ may be seen as a 'catch all' variable for cross-sectional dependence, which has not been accounted

[2] As Fisher and Griffith (2008) point out, for row standardized matrices the row sums of W are bounded uniformly in absolute value by one, so that the Perron–Forbenius theorem states that $\lambda_{\max} = 1$ and $-1 \leq \lambda_{\min}$.

for by the spatial lags of the exogenous variables. In a hierarchical manner, further restrictions to both the SDM and SDEM can be imposed yielding the

- spatial lag (or autoregressive) model (SAR) with $\lambda = 0$ and $\sum_{m=1} \gamma_m = 0$ as a restricted form of the SDM $\rightarrow$ SAR and
- spatial error model (SEM) with $\rho = 0$, $\phi = 0$ and $\sum_{m=1} \gamma_m = 0$ as restricted form of the SDEM $\rightarrow$ SEM.

For the remainder of this paper we concentrate on specifications based on the spatial lag (SAR) and spatial Durbin model (SDM) approach.[3] Especially the latter model may be seen as a general modelling framework, which allows to test for the validity of different restrictions (see also Mur and Angulo 2006; Elhorst 2010).

Similar to the concept of the lagged endogenous variable in time series analysis, the estimated spatial lag coefficients characterize a contemporaneous correlation between one cross-sectional observation and geographically proximate units for the same variable. The spatial lag coefficient of the dependent variable, for instance, measures the effect of the weighted average of the neighborhood of cross-section i as $\sum_{j=1}^{n} w_{ij} \times y_{j,t}$. Additionally, the inclusion of further spatial lags of exogenous variables allows for the possibility of spatial spillovers. With respect to the included time and spatial lags of the endogenous variables in (4.2), we can distinguish between ‘space–time recursive’, ‘dynamic’ and ‘simultaneous’ combinations (see Anselin et al. 2007). In the following, we restrict our analysis to the ‘space–time simultaneous’ model, which sets $\phi = 0$ but includes a time and spatial lag of the dependent variable. As Parent and LeSage (2009) point out, the latter restriction imposes $\omega = -\rho \times \alpha = 0$. This implies that all explicitly modelled spatial effects are assumed to take place within each time period of observation.

However, given our chosen specification based on a time lag and a contemporaneous spatial lag of the dependent variable, the model indirectly also captures the effects of time lags for $\sum_{j \neq i} w_{ij} \times y_j$ as summarized in Fig. 4.1. These latter indirect effects are due to the fact that the right hand side regressors $y_{i,t-1}$ and $\sum_{j \neq i} w_{ij} \times y_{j,t}$ for each point in time are likewise a function of past values of the spatial lags of the dependent variable. This, in turn, should partially capture the gradual adjustment process of spatial neighborhood effects. At the same time, by using the space–time simultaneous specification we avoid the potential multicollinearity problem arising from the joint inclusion of the dependent variable’s time lag and past values of its spatial lags as right-hand-side regressors. We do not put any particular restriction on the space–time dynamics of the exogenous variables included in our model.

The choice of the (time) lag length for own values and spatial lags of the dependent variable has important implications for the formulation of valid moment conditions in the course of GMM estimation (see Bouayad-Agha and Vedrine 2010).

[3] Details about time dynamic panel data estimators of the spatial error type model are e.g. given in Mutl (2006). The author derives a multi step estimation strategy for the Arellano–Bond (1991) type GMM estimator based on a consistent estimator of the spatial autoregressive parameter as proposed in Kapoor et al. (2007).

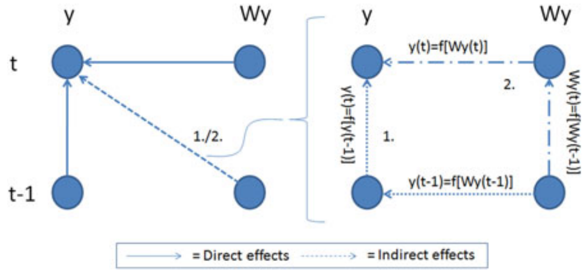


Fig. 4.1 Direct and indirect effects of the space–time simultaneous migration equation

This is due to the fact that the spatial lag term of the endogenous variable is correlated with the model's composed error term (see e.g. Kukenova and Monteiro 2008). From an econometric point we thus have to treat this term as endogenous (in analogy to the time autoregressive component in the DPD context). The solution of GMM based estimators is then to obtain an estimate for ρ by means of appropriate instrumental variables in the context of the Arellano–Bond (1991) or Blundell–Bond (1998) SYS-GMM estimator. Focusing on the latter estimator, consistent instruments can be derived from the so-called 'standard' and 'stationarity' moment conditions. The former condition builds upon the seminal contribution in Anderson and Hsiao (1981) extended to the GMM framework by Arellano and Bond (1991), and estimate an aspatial DPD model as in (4.1) transformed into first differences based on the following moment condition

$$E(y_{i,t-s}\,\Delta u_{i,t}) = 0, \quad t = 3,\dots,T,\ s = 2,\dots,t-1, \tag{4.5}$$

which employs sufficient lags of the endogenous variable in levels (starting from $y_{i,t-2}$) to serve as own instruments for $\Delta y_{i,t-1}$ in the first differenced equation (for details see Arellano and Bond 1991). Additionally, the model can be augmented by appropriate instruments in first differences for the equation in levels, making use of the stationarity moment condition as (see e.g. Arellano and Bover 1995; Ahn and Schmidt 1995, and Blundell and Bond 1998):

$$E(\Delta y_{i,t-1}\,u_{i,t}) = 0, \quad t = 3,\dots,T. \tag{4.6}$$

The 'stationarity' moment condition in (4.6) rests on certain assumptions about the initial period observation $y_{i,0}$ for panel data settings with only few time periods. Both in the pure panel time-series as well space–time panel literature the importance of the initial condition has been stressed (see e.g. Parent and LeSage 2009). Rather than taking the initial period observation as given (see e.g. Elhorst 2005, for an ML estimator with exogenous $y_{i,0}$), the GMM literature typically assumes mean stationarity of $y_{i,0}$ based on the following assumption for its data generating process $y_{i,0} = \mu_i/(1-\alpha) + \xi_{i,0}$ with $E(\mu_i\,\xi_{i,0}) = 0$ and $E(\xi_{i,0}\,\nu_{i,t}) = 0$ (for further details see e.g. Hsiao 2003).[4] Further instruments beside those derived from sufficiently

[4]One also has to note that (4.6) is derived as a linearization of the original stationarity condition proposed by Ahn and Schmidt (1995) from a set of non-linear conditions given by $E(\Delta y_{i,t-1} u_{i,T}) = 0$ for $t = 3,\dots,T$.

long time lags for the endogenous variable may also be derived from each explanatory variable x, where the set of valid instruments for each variable depends on its correlation with respect to the error term. The consistency of moment conditions based on y and x can generally be tested with the help of overidentification tests such as Hansen's (1982) J-statistic and the Difference-in Hansen's J-statistic. The latter also allows to test on the validity of the level equation in the addition to the first difference equation according to the Arellano–Bond (1991) GMM estimator.

Augmenting the instrument set by transformations of $x_{i,t}$, then the following moment conditions apply for the first differenced equation:

- If $x_{i,t}$ is strictly exogenous,

$$E(x_{i,t\pm s}\,\Delta u_{i,t}) = 0, \quad t = 3, \dots, T\ \forall s. \tag{4.7}$$

- If $x_{i,t}$ is weakly endogenous (predetermined),

$$E(x_{i,t-s}\,\Delta u_{i,t}) = 0, \quad t = 3, \dots, T,\ s = 1, \dots, t-1. \tag{4.8}$$

- If $x_{i,t}$ is strictly endogenous,

$$E(x_{i,t-s}\,\Delta u_{i,t}) = 0, \quad t = 3, \dots, T,\ s = 2, \dots, t-1. \tag{4.9}$$

For the level equation of the SYS-GMM estimator in (4.6) we may formulate valid moment conditions as:

- If $x_{i,t}$ is strictly exogenous,

$$E(\Delta x_{i,t}\,u_{i,t}) = 0, \quad t = 2, \dots, T. \tag{4.10}$$

- If $x_{i,t}$ is weakly or strictly endogenous

$$E(\Delta x_{i,t-1}\,u_{i,t}) = 0, \quad t = 3, \dots, T. \tag{4.11}$$

The SYS-GMM estimator then jointly employs both (4.5) and (4.6) for estimation. Though labeled 'system' GMM, the estimator in fact treats the (stacked) data system as a single-equation problem since the same linear functional relationship is believed to apply in both the transformed and untransformed variables as:

$$\begin{pmatrix}\Delta y\\ y\end{pmatrix} = \alpha\begin{pmatrix}\Delta y_{-1}\\ y_{-1}\end{pmatrix} + \rho\begin{pmatrix}\Delta WY\\ WY\end{pmatrix} + \beta\begin{pmatrix}\Delta X_{-1}\\ X_{-1}\end{pmatrix} + \begin{pmatrix}\Delta u\\ u\end{pmatrix}. \tag{4.12}$$

For the spatially augmented SYS-GMM specification, equivalent moment conditions can likewise be derived from the spatial lag term of the dependent and explanatory variables. Since the spatial lag of the dependent variable is endogenous in (4.2), a natural means for estimation of the SYS-GMM estimator is to build internal instruments using time lags for both the equation in first differences as well as levels. Moreover, as Bouayad-Agha and Vedrine (2010) point out, we can make use of spatially weighted exogenous $x_{i,t}$ variables to instrument $\sum_{i\neq j} w_{ij} \times y_{i,t-s}$. The latter attempt aims at identifying the exogenous part of the spatial lag variability by means of a spatially weighted model. Assuming strict exogeneity of current and lagged values for $x_{i,t}$, then the full set of potential moment conditions for the spatial lag of $y_{i,t-1}$ is given by

- First differenced equation:

$$E\left(\sum_{i\neq j} w_{ij} \times y_{i,t-s} \quad \Delta u_{i,t}\right) = 0, \quad t = 3, \ldots, T, \; s = 2, \ldots, t-1, \tag{4.13}$$

$$E\left(\sum_{i\neq j} w_{ij} \times x_{i,t \pm s} \quad \Delta u_{i,t}\right) = 0, \quad t = 3, \ldots, T \;\forall s. \tag{4.14}$$

- Level equation:

$$E\left(\sum_{i\neq j} w_{ij} \times \Delta y_{i,t-1} \quad u_{i,t}\right) = 0, \quad t = 3, \ldots, T, \tag{4.15}$$

$$E\left(\sum_{i\neq j} w_{ij} \times \Delta x_{i,t} \quad u_{i,t}\right) = 0, \quad t = 2, \ldots, T. \tag{4.16}$$

One has to note that the consistency of the SYS-GMM estimator relies on the validity of these moment conditions. Moreover, in empirical application we have to carefully account for the 'many' and/or 'weak instrument' problem typically associated with GMM estimation, since the instrument count grows as the sample size T rises. We thus put special attention to this problem and use restriction rules specifying the maximum number of instruments employed as e.g. proposed by Bowsher (2002) and Roodman (2009).

Accounting for spatial lags of the endogenous and exogenous variables leads to the SDM representation of the neoclassical migration model from (4.1). We can write the model in its full triple indexed form as

$$\begin{aligned}
nm_{ij,t} = {} & \alpha nm_{ij,t-1} + \rho \sum_{r,s\neq i,j} w(i,j;r,s) \times nm_{ij,t-1} \\
& + \beta_1 \widetilde{wr}_{ij,t-1} + \gamma_1 \sum_{r,s\neq i,j} w(i,j;r,s) \times \widetilde{wr}_{ij,t-1} \\
& + \beta_2 \widetilde{ur}_{ij,t-1} + \gamma_2 \sum_{r,s\neq i,j} w(i,j;r,s) \times \widetilde{ur}_{ij,t-1} \\
& + \beta_3 \widetilde{ylr}_{ij,t-1} + \gamma_3 \sum_{r,s\neq i,j} w(i,j;r,s) \times \widetilde{ylr}_{ij,t-1} \\
& + \beta_4 \tilde{q}_{ij,t-1} + \gamma_4 \sum_{r,s\neq i,j} w(i,j;r,s) \times \tilde{q}_{ij,t-1} \\
& + \beta_5 \widetilde{hc}_{ij,t-1} + \gamma_5 \sum_{r,s\neq i,j} w(i,j;r,s) \times \widetilde{hc}_{ij,t-1} \\
& + \beta_6 \widetilde{\Delta p^l}_{ij,t-1} + \gamma_6 \sum_{r,s\neq i,j} w(i,j;r,s) \times \widetilde{\Delta p^l}_{ij,t-1} + \mu_{ij} + \nu_{ij,t},
\end{aligned} \tag{4.17}$$

where the elements of the spatial weighting matrix w are now defined in a four dimensional space of origin-destination linkages varying by i, j, r and s, where i and r denote flow origins and j and s flow destinations, respectively (all of dimension N for each t). Each element $w(i, j; r, s)$ of the spatial weighting matrix thus defines whether two origin destination pairs (i, j) and (r, s) are neighboring observations or not. In the following, we will discuss how to design spatial dependency schemes for this network structure.

4.2.3 Imposing Spatial Dependency Structures for Migration Flows

In order to properly account for any form of spatial autocorrelation, we will analyze migration flows in the context of network structures, where individual flows are assumed to be related to one another. The relationship among network flows can then be arranged in a spatial weighting matrix. However, while a standard spatial weighting matrix typically has an $n \times n$ dimension for an underlying tessellation containing n spatial regions, the dimension of a spatial network matrix becomes $(n^2 \times n^2)$.[5] As Fisher and Griffith (2008) point out, we thus need to shift attention from a two–dimensional space for n regions and $n \times n$ origin (i), destination (j) pairs $\{i, j | i \neq j; i, j = 1, \ldots, n\}$ to a four dimensional space with $n^2 \times n^2$ origin-destination linkages $\{i, j, r, s | i \neq j, r \neq s; i, j = 1 \ldots, n; r, s = 1, \ldots, n\}$. An appropriate spatial weighting matrix (W^*) should then be able to jointly capture a set of origin related interaction effects (W^o) and a set of destination interaction effects (W^d) as

$$W^* = W^o + W^d. \tag{4.18}$$

The elements w^o of the origin-based spatial weights matrix W^o can be defined as

$$w^o(i, j; r, s) = \begin{cases} 1 & \text{if } j = s \text{ and } c(i, r) = 1, \\ 0 & \text{otherwise,} \end{cases} \tag{4.19}$$

where $c(i, r)$ is the element of a conventional $(n \times n)$ link matrix with

$$c(i, r) = \begin{cases} 1 & \text{if } i \neq r \text{ and } i \text{ and } r \text{ are spatially linked to each other,} \\ 0 & \text{otherwise.} \end{cases} \tag{4.20}$$

In this framework, the spatial link between origins i and r may either be measured in terms of a common border or equivalently by defining a threshold distance and operationalize it in a binary way for i and r to be linked. The spatial weights matrix W^o thus specifies an origin-based neighborhood set for each origin-destination pair (i,j). According to Fisher and Griffith (2008) each element $w^o(i, j; r, s)$ defines an origin-destination pair (r,s) as being a neighbor of (i,j) if the origin regions i

[5] Giving that migration data typically abstracts from intraregional flows, our spatial weighting matrix is defined as a non-negative symmetric matrix of the form $[(n^2 - n) \times (n^2 - n)]$.

and r are contiguous spatial units and $j = s$. In similar veins, the specification of the destination based spatial weights matrix W^d consists of the following elements w^d as

$$w^d(i, j; r, s) = \begin{cases} 1 & \text{if } i = r \text{ and } c(j, s) = 1, \\ 0 & \text{otherwise,} \end{cases} \tag{4.21}$$

where

$$c(j, s) = \begin{cases} 1 & \text{if } j \neq s \text{ and } j \text{ and } s \text{ are spatially linked to each other,} \\ 0 & \text{otherwise.} \end{cases} \tag{4.22}$$

The full weighting matrix W^* can be used in its binary—or alternatively—row-standardized form. Since we are dealing with panel data, we finally have to stack the obtained weighting matrix first ordered by time and then by cross-section (so that N is the faster index) according to

$$W_{NT}^* = \begin{bmatrix} W_1^* & \cdots & 0 & 0 \\ 0 & W_2^* & \cdots & 0 \\ \vdots & \vdots & \ddots & \vdots \\ 0 & 0 & \cdots & W_T^* \end{bmatrix}, \tag{4.23}$$

where W_t^* is the $N \times N$ spatial weighting matrix for period t. For the most general case, W_t^* is allowed to vary with each time period, e.g. due to missing data or changes in the distance between two observations. If W_t^* is identical for the whole sample period, W_{NT}^* can easily computed as $W_t^* \otimes I_T$, where I_T is the identity matrix of order T.

An important prerequisite for empirical application is that the spatial lag variables can be given an theoretical interpretation. Here, Chun (2008) argues that the design W^* can be motivated by theoretical concepts that map migration flows from a origin- and destination-related perspective. In this logic the specification of W^o—linking network flows from spatially linked origins to one particular destinations—is supposed to mirror the effect of intervening opportunities in the path of migratory movements from an origin to a pre-selected destination. Movements of people in space are modelled upon the idea that the number of migration flows between two regions is determined by the availability of different intervening opportunities (such as the number of available jobs etc.) existing between the origin and the destination. Under the assumption that migrants move as short a distance as possible, the intervening opportunities model then provides a behavioral argument of spatial search in sequential form, where the spatial arrangement of regions—predominately around an origin—has great influence on the number of potential intervening opportunities (for details see e.g. Freymeyer and Ritchey 1985; Chun 2008). Thus, given that intervening opportunities exist in regions that are located between an origin and destination, migration flows to one particular destination from a number of origins, which are spatially close to each other, are likely to be correlated.

Likewise, the specification of the destination-related weighting matrix W^d in (4.21) and (4.22) can be motivated by competing destinations effects from the perspective of a particular origin region (see e.g. Fotheringham 1983; Hu and Pooler 2002). The basic idea of the competing destinations approach is to model human behavior as a spatial choice process based on the assumption that the actual choice occurs through hierarchical information processing since migrants are supposed to be only able to evaluate a limited number of alternative at a time. Hence, prospective migrants tend to simplify the alternatives by categorizing all alternatives into clusters, where the probability that one destination in a certain cluster will be chosen is related to the other regions in that cluster. This clustering effect in turn requires that spatial proximity of destinations has an influence on the destination choice of migrants from one particular origin. The competing destinations approach reflects a two-stage decision process, where the attractiveness of all defined groups of destinations is evaluated and a particular group is chosen in a first step. In the second step then the individual destination will be selected out of this group.

For empirical application it is reasonable to assume that both effects are in order and operate simultaneously so that the aggregated weight matrix W^* may be an appropriate choice for analyzing the range of cumulative network effects in migration flows. Recent research results dealing with closely related modes of network modelling generally support this view.[6] Throughout the rest of the paper we will thus use the combined weight matrix W^* in order to capture network autocorrelation effects in German migration flows.

4.3 Stylized Facts and Exploratory Space–Time Data Analysis

German interregional migration data tracks the movement of all residents in Germany. For the empirical analysis we use annual data for the 16 German states between 1991 and 2006. All monetary variables are denoted in real terms. A full description of the variable definitions and data sources is given in Table 4.1. To check for the space–time properties of migration flow data we first account for their underlying time series properties. Based on the Im–Pesaran–Shin (2003) and Pesaran (2007) panel unit roots test we find that for all variables we can reject the null hypothesis of non-stationarity for reasonable confidence levels (see Table 4.2).[7] Migration flows may thus be seen as transitory movements to restore multiregional labor market equilibria.

Turning to the stylized facts of German internal migration, Fig. 4.2 displays scatter plots for in- and out-migration flows of German states for four sample years 1991, 1996, 2001 and 2006. The interpretation of the figure is straightforward: The closer data points are to the diagonal (45-degree line), the more balanced are their

[6] See, e.g. Guldmann (1999), Almeida and Goncalves (2001), Hu and Pooler 2002, and LeSage and Pace (2008) among others. LeSage and Pace (2008) additionally discuss the impact on regression results if either W^* or separate matrices for W^o and W^d are included in the spatial model.

[7] The latter approach by Pesaran (2007) has the advantage that it is relatively robust with respect to cross-sectional dependence in the variable, even if the autoregressive parameter is high (see e.g. Baltagi et al. 2007, as well as de Silva et al. 2009, for extensive Monte Carlo simulation evidence).

Table 4.1 Data description and source

Variable	Description	Source
$outm_{ijt}$	Total number of out-migration from region i to j	Destatis (2008)
inm_{ijt}	Total number of in-migration from region i to j	Destatis (2008)
$y_{i(j)t}$	Gross domestic product in region i and j respectively	VGRdL (2008)
$py_{i(j)t}$	GDP deflator in region i and j respectively	VGRdL (2008)
$ylr_{i(j)t}$	Real labor productivity defined as $(yl_{j,t} - py_{j,t})$	VGRdL (2008)
$pop_{i(j)t}$	Population in region i and j respectively	VGRdL (2008)
$emp_{i(j)t}$	Total employment in region i and j respectively	VGRdL (2008)
$unemp_{i(j)t}$	Total unemployment in region i and j respectively	VGRdL (2008)
$ur_{i(j)t}$	Unemployment rate in region i and j respectively defined as $(unemp_{i,t} - emp_{i,t})$	VGRdL (2008)
$pcpi_{i(j)t}$	Consumer price index in region i and j respectively based on Roos (2006) and regional CPI inflation rates	Roos (2006), RWI (2007)
$wr_{i(j)t}$	Real wage rate in region i and j respectively defined as wage compensation per employee deflated by $pcpi_{i(j)t}$	VGRdL (2008)
$q_{i(j)t}$	Labor market participation rate in region i and j respectively defined as $(emp_{i,t} - pop_{i,t})$	VGRdL (2008)
$hc_{i(j)t}$	Human capital index as weighted average of: 1) high school graduates with university qualification per total pop. between 18–20 years (*hcschool*), 2) number of university degrees per total pop. between 25–30 years (*hcuni*), 3) share of employed persons with a university degree relative to total employment (*hcsvh*), 4) number of patents per pop. (*hcpat*): $hc = 0.25 * hcsvh + 0.25 * hcschool + 0.25 * hcuni + 0.25 * hcpat$	Destatis (2008)
$p^l_{i(j)t}$	Average price for building land per qm in i and j, in Euro	Destatis (2008)

Note: All variables in logs. For Bremen, Hamburg and Schleswig-Holstein no consumer price inflation rates are available. We took the West German aggregate for these states, this also accounts for Rhineland-Palatine and Saarland until 1995. In order to construct time series for the price of building land (p^l) no state level data before 1995 was available. Here we used the 1995–1999 average growth rate for each state to derive the values for 1991–1994. For Hamburg and Berlin only very few data points were available. Here we took the price per qm in 2006 and used national growth rates to construct artificial time series

net migration patterns: For data points on the diagonal net migration is equal to zero, while the area above (below) the diagonal indicate positive (negative) net migration flows. Data points closer to the origin inhibit smaller gross migration volumes and vice versa. The figure additionally accounts for population size by weighting the size of the data point (circle) with its absolute population value for the respective period. The figure confirms the tendency that populous states on average have higher absolute gross migration flows (moving towards the upper right of the scatter plot).

Table 4.2 Im et al. (2003) IPS and Pesaran (2007) CADF panel unit root test for variables

Specification	IPS and CADF tests for $N \times (N-1)$, $T = (240, 16)$			
	H_0: All cross-sections contain unit roots			
	$\overline{IPS}$	p-value	$\overline{CADF}$	p-value
$nm_{ij,t}$	−16.75	(0.00)	−9.61	(0.00)
$\widetilde{ur}_{ij,t}$	−17.69	(0.00)	−12.82	(0.00)
$\widetilde{wr}_{ij,t}$	−96.09	(0.00)	−8.35	(0.00)
$\Delta \widetilde{ylr}_{ij,t}$	−67.42	(0.00)	−28.35	(0.00)
$\widetilde{q}_{ij,t}$	−15.59	(0.00)	−7.57	(0.00)
$\widetilde{hc}_{ij,t}$	−21.56	(0.00)	−5.00	(0.00)

Note: Including a constant term; optimal (average) lag length selection for the IPS test according to the AIC. The same lag length was then imposed for the CADF test

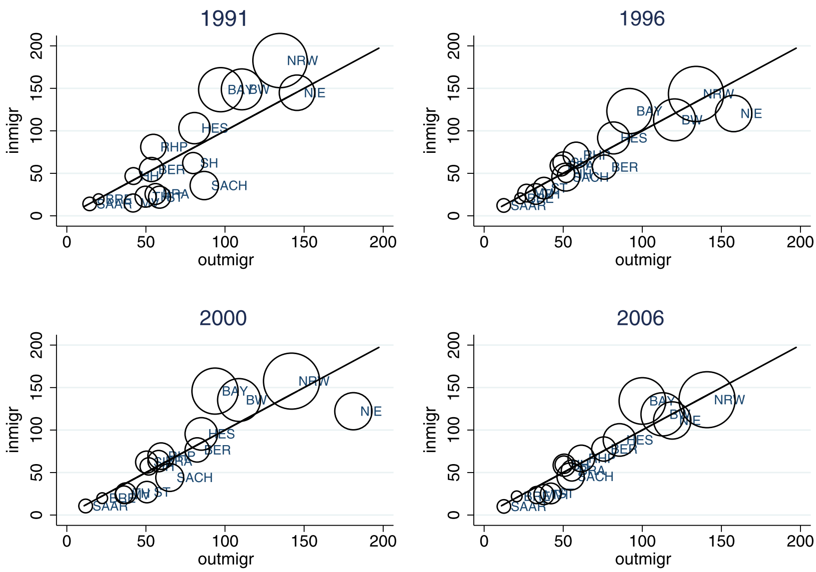


Fig. 4.2 Weighted scatter plots for state level in- and out-migration. *Source*: Data from Detstatis (2008). *Note*: BW = Baden-Württemberg, BAY = Bavaria, BER = Berlin, BRA = Brandenburg, BRE = Bremen, HH = Hamburg, HES = Hessen, MV = Mecklenburg-Vorpommern, NIE = Lower Saxony, NRW = North Rhine-Westphalia, RHP = Rhineland-Palatine, SAAR = Saarland, SACH = Saxony, ST = Saxony-Anhalt, SH = Schleswig-Holstein, TH = Thuringia

Starting in 1991, Fig. 4.2 shows that all East German states are clearly below the 45°-diagonal line indicating population losses with Saxony being hit the most. This underlines that alongside economic transformation the East German states have witnessed a substantial loss of population through East–West net out-migration West German states are either on or above the diagonal line indicating net migration inflows. This strong migration response to German re-unification is less present in 1996, where all state values are much closer to the diagonal. However, in 2001 a second wave of increased East–West out-migration can be observed.[8] Towards the sample end in 2006 interregional migration flows among German states again seem to be more balanced than in the early 1990s and around 2001.

Analyzing migration flows in the context of network structures allows to identify the (most) significant flows among the full migration matrix for a given time period. Therefore, Fig. 4.3 highlights the 10% and 25% largest network flows among all migratory movements for two chosen sample years (1991 and 2001). The results for 1991 show, that the 10% most prominent flows are predominantly driven by large East–West migratory movements after German re-unification. Next to the dominant East–West pattern there are also significant North–South movements with large net out-migration flows from Schleswig-Holstein (SH) and Lower Saxony (NIE). If we additionally include major migration flows up to the 25% level in the upper right graph of Fig. 4.3, the distinct East–West net out-migration trend becomes even more visible. Though the latter trend is also shown for migratory movements in 2001, now flows are much more directed towards the southern states in Germany. The latter shift in turn may reflect the migration response to their much better economic performance throughout the late 1990s compared to other (Western) states such as North-Rhine Westphalia.

Finally, the graphical network presentation of Fig. 4.3 also gives first empirical support that migration flows indeed correlate with the chosen pattern of our spatial weighting scheme: Taking net migration flows for Saxony-Anhalt (ST) in 2001 as an example, we see that the state has a large net outflow to Bavaria (among the 10% most significant flows). However, not only Saxony-Anhalt also the Eastern (Brandenburg, Saxony, Thuringia) and Western states (Lower Saxony) in the geographical neighborhood of Saxony-Anhalt have significant outflows directed to Bavaria. If we take the common border criteria as a measure of spatially linked regions, the spatial autocorrelation pattern inhibit in these flows is well captured by the origin-related weighting matrix in the definition (4.19) and (4.20) reflecting the intervening opportunities approach of migration modelling. Likewise, if we look at the 10% significant outflows of Brandenburg (BRA) for 2001, these are both directed to the southern states Bavaria and Baden-Württemberg, which themselves share a common border. The underlying network paradigm can now be described in terms of the destination-based weighting scheme according to (4.21) and (4.22) mirroring the migrant's choice process in space.

The graphical presentation of major migration flows in Fig. 4.3 already provides a first indication of the likely importance of spatial autocorrelation. As a more formal inspection of the underlying space–time dependencies we apply different tools

[8] The strong negative outlier effect of the West German state Lower Saxony (Niedersachsen) is due to the specific migration pattern of German resettlers from Eastern and Southern Europe (Spätaussiedler), which are legally obligated to first move to the central base Friesland in Lower Saxony and only subsequently migrate to other states. Hence, taking also external migration for Niedersachsen into account this negative effect vanishes.

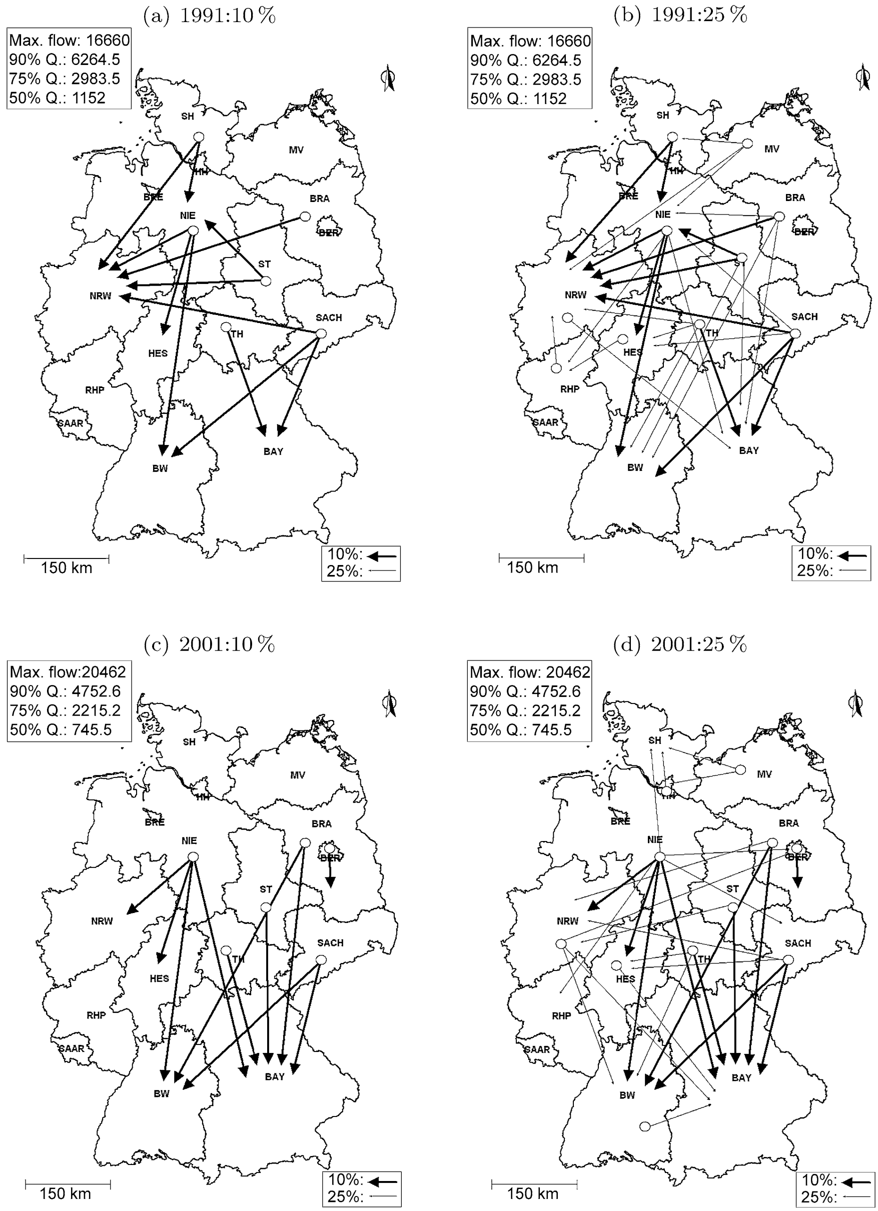


Fig. 4.3 Prominent migration flows between German states in 1991 and 2001

of exploratory space–time data analysis (ESTDA). The most commonly applied indicator to detect spatial autocorrelation among values of a particular variable is the Moran's I statistic. However, for a full space–time analysis the latter statistic cannot be applied directly since it is only defined for the analysis of cross-sectional data. Here, we thus make use of straightforward extensions of Moran's I, which are able to account for time lags on the one hand as well as pool data for different time periods within a common statistic on the other hand. Earlier Moran's I based space–time indices (thereafter, *STMI*) have already been proposed by Cliff and Ord (1981) as well as Griffith (1981).

The STMI indices allow to compare the pairwise correlation between observations of a variable and its spatial lag, when the time dimension for one of the two observations is altered while the other one is held fixed at time t (e.g. by the inclusion of different time lags). This allows giving a first indication of the diffusion of spatial dependence over time. Recently, Lopez et al. (2010) have additionally demonstrated that these space–time indices can also be applied to panel data after some straightforward transformations. Moreover, the authors have shown by means of Monte Carlo simulations that the pooled $STMI_P$ (where the subscript 'P' indicates the pooling of cross-sections over time) has a satisfactory small sample behavior compared to other spatialized statistics such as the Brett and Pinkse (1997) or the Lagrange multiplier test. A formal definition of the Moran's I based individual and pooled space–time statistics is given in Appendix A.

To apply these ESTDA tools to our migration data, we also need an operationalization of the spatial weighting matrix W^*_{NT} besides the proper space–time autocorrelation statistic. Here, we compare the empirical performance of two different types of weighting schemes: 1) Spatial links are defined by a link function based on common borders between states, 2) We use an optimal distance criterion which assigns two regions a neighbors if they fall into a maximum distance band derived from a maximization procedure for the Getis and Ord (1992) G-statistic (computational details are given in Appendix B. Distance between to states is thereby calculated as the road distance in kilometers between a population weighted average of major city pairs for each pairwise combination of regions. A detailed list of the cities included in the sample and the resulting distance matrix are given in Appendix B. Table 4.3 reports the results of the Moran's I statistic for each individual year as well as the pooled space–time Moran's I statistic as $STMI_P(t-k)$ with $k=0$.

As the table shows, both for each individual year as well as for the joint sample period we detect a highly significant spatial autocorrelation pattern. Figure 4.4 additionally plots the results of the $STMI_P$ graphically based on a regression of the standardized migration variable (using the optimal distance based spatial weighting scheme). The slope coefficient is identical to the calculated $STMI_P$. Additionally, the regression framework allows testing for the presence of time fixed effects, that is, whether spatial dependence alters significantly over the sample period. To do so, we include a set of year dummies in the regression approach and test for their joint significance. The results of the underlying F-test do not reject the null hypothesis of poolability over the time periods with $F(15,3823)=0.74$ (p-value: 0.75).

Finally, we aim to gain further insight into the role of space–time interdependencies in migration flows by calculating the year-specific *STMI* for different lag structures as well as its pooled counterpart. Figure 4.5 first presents the results of the $STMI(t-k)$ based surface analysis as pairwise spatial correlation analysis over the whole sample period. Here, the diagonal elements are the $I(t)$ values for each

Table 4.3 Moran's I and $STMI_P(t)$ statistic for net migration rate

Year	Common border		Optimal distance		
	Coef.	p-value	d	Coef.	p-value
1991	0.306***	(0.00)	250	0.297***	(0.00)
1992	0.536***	(0.00)	250	0.509***	(0.00)
1993	0.556***	(0.00)	275	0.514***	(0.00)
1994	0.745***	(0.00)	275	0.678***	(0.00)
1995	0.665***	(0.00)	350	0.616***	(0.00)
1996	0.646***	(0.00)	350	0.668***	(0.00)
1997	0.659***	(0.00)	350	0.671***	(0.00)
1998	0.713***	(0.00)	350	0.691***	(0.00)
1999	0.610***	(0.00)	275	0.593***	(0.00)
2000	0.597***	(0.00)	275	0.545***	(0.00)
2001	0.480***	(0.00)	275	0.471***	(0.00)
2002	0.512***	(0.00)	275	0.483***	(0.00)
2003	0.601***	(0.00)	275	0.593***	(0.00)
2004	0.557***	(0.00)	275	0.553***	(0.00)
2005	0.679***	(0.00)	275	0.599***	(0.00)
2006	0.616***	(0.00)	250	0.601***	(0.00)
$STMI_P(t)$	0.538***	(0.00)		0.501***	(0.00)

Note: d denotes the optimal distance maximizing the absolute sum of the (local) $G_i(d)$-statistic and is measured in kilometers per fixed units of 25 km each

*Denote statistical significance at the 10% level

**Denote statistical significance at the 5% level

***Denote statistical significance at the 1% level

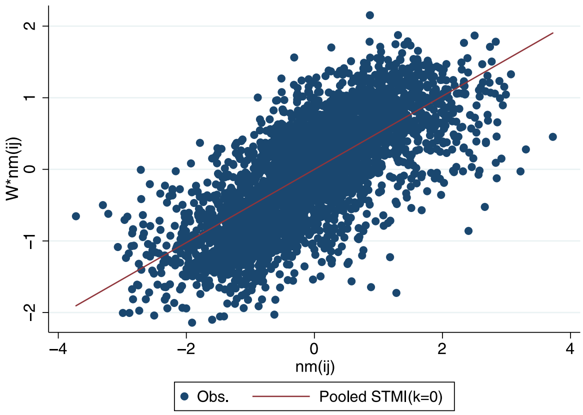


Fig. 4.4 Bivariate scatterplot for $STMI_P$ for $k = 0$

individual year, values below the diagonal report $STMI_{t-k}$ values with an increasing lag structure, which relate the spatial lag of net migration at time t to past values of the original variable. As can be seen, the highest values for spatial autocorrelation are more or less concentrated in—or nearby—the diagonal line. With increasing lag length spatial dependence gradually fades out, which hints at the existence of a

Fig. 4.5 $STMI(t-k)$ surface plot for net migration rate

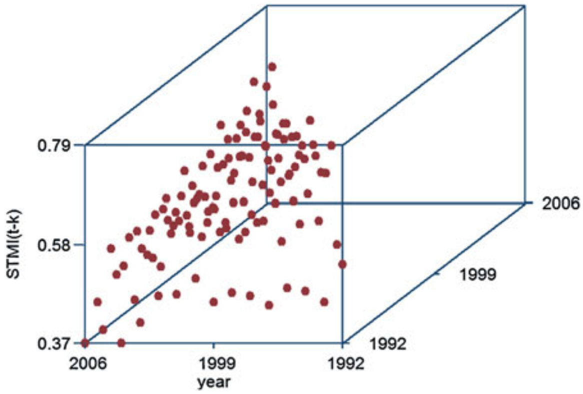
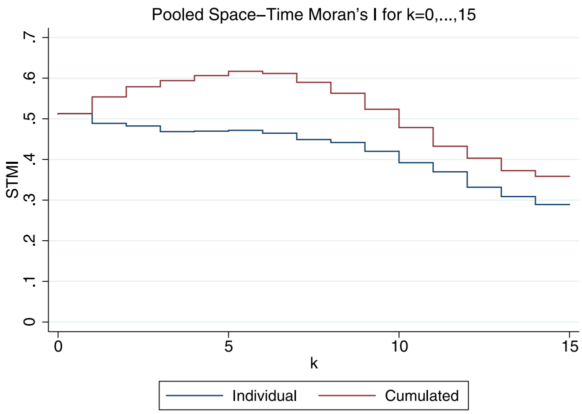


Fig. 4.6 $STMI_P(t-k)$ values for different lag length k



strong contemporaneous spatial dependence effect in migration flows. Nevertheless, even for higher lag lengths spatial correlation does not fully cancel out.

This impression is also supported by Fig. 4.6, which plots the pooled $STMI_P(t-k)$ statistic for different lag length k (both individually as well as cumulated over all available lags). The individual $STMI_P(t-k)$ pattern thereby shows that spatial autocorrelation is the highest for the contemporaneous case with $k=0$ and fades out with higher lag length. As Lopez and Chasco (2005) argue, the decreasing trend in this function points towards a steady space–time diffusion (compared to the case of an increasing or absent time trend). Looking at the cumulated 'long run' effect when calculating the $STMI_P(t-k)$ based on all available lags, the resulting time series follows a similar pattern. Nevertheless, the overall maximum for $STMI_P(t-k)$ is only slightly higher compared to the contemporaneous case with $k=0$. This indicates that spatial structure is rather stable over time and gives empirical support to the appropriateness of our chosen space–time simultaneous model, which shows to capture most of the spatial interdependencies present in the data set. Moreover, as Lopez and Chasco (2007) show by means of Monte Carlo simulations, the statistical capacity to properly identify and discriminate between different space–time processes declines with increasing temporal correlation, which additionally supports the choice of a space–time simultaneous model.

4.4 Empirical Results of the Spatial Regression Approach

The regression results for the aspatial benchmark model from (4.1) and subsequent spatial extensions according to (4.17) are shown in Table 4.4. Beside the spatial lag specification of the extended SYS-GMM approach we also report regression results from standard SYS-GMM estimation after variables have been spatially filtered using a method proposed by Getis (1995). Spatial filtering treats cross-sectional dependence in the data as a nuisance parameter and as entirely independent of the underlying 'spaceless' model to be estimated.[9] For both the aspatial, spatial filtered and spatial lag regression models we report the estimated variable coefficients together with two important types of post estimation tests: A primary concern is to carefully check for the instrument consistency of the chosen specification. We therefore guide instrument selection based on the widely applied Sargan (1958)/Hansen (1982) overidentification test (J-statistic) as well as the C-statistic (or also 'Diff-in-Sargan/Hansen') as numerical difference of two J-statistics isolating IV(s) under suspicion of being endogenous (see Eichenbaum et al. 1988, for details).

In an overidentified model the J-statistic allows to test whether the model satisfies the full set of moment conditions, while a rejection implies that IVs do not satisfy orthogonality conditions required for their employment. In similar veins, the C-statistic may be used to judge about the consistency of the additional instrument set in the level equation (testing the SYS-GMM model against its Arellano–Bond (1991) type first differenced counterpart). A second type of postestimation tests explicitly looks at the likely bias introduced by spatial autocorrelation in the residuals of the empirical models. Here we compute residual based Moran's I statistics for each individual year and in its pooled version ($STMI_P$), as well as a Wald GMM test for spatial autocorrelation in the model's error term (see Kelejian and Prucha 1999; Egger et al. 2005). Egger et al. (2005) show on the basis of Monte Carlo simulations that GMM based Wald tests tend to perform well irrespective of the underlying error distribution and thus are a well-equipped alternative to the frequently used Moran's I test under GMM circumstances. Both postestimation tests give important hints to identify misspecifications in the empirical modelling approach.

The aspatial migration equation in column I of Table 4.4 serves as a general benchmark for the spatially augmented specifications. For most variables we find statistically significant coefficients in line with the theoretical predictions of the neoclassical migration model, e.g. a real wage increase in region i relative to region j leads to increased net in-migration flows, while a relative increase in the regional unemployment rate has the opposite effect. Turning to the postestimation

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[9] A detailed description of the spatial filtering approach based on Getis (1995) is given in Appendix B.

Table 4.4 Estimation results of the dynamic migration model using spatial filtering and spatial lag model

DPD model:	Aspatial	Spatial filtering		Spatial lag model			
Weights matrix:	None	Border	Distance	Border	Distance	Border	Distance
	I	II	III	IV	V	VI	VII
$nm_{ij,t-1}$	0.51***	0.39***	0.36***	0.26***	0.30***	0.43***	0.40***
	(0.044)	(0.072)	(0.048)	(0.058)	(0.053)	(0.071)	(0.063)
$\widetilde{wr}_{ij,t-1}$	0.21**	0.33**	0.39***	0.39***	0.36***	0.32***	0.30***
	(0.042)	(0.141)	(0.121)	(0.118)	(0.108)	(0.111)	(0.105)
$\widetilde{ur}_{ij,t-1}$	−0.16***	−0.09	−0.09	−0.01	−0.04	−0.08*	−0.08**
	(0.042)	(0.077)	(0.067)	(0.057)	(0.045)	(0.046)	(0.043)
$\Delta\widetilde{ylr}_{ij,t-1}$	0.55***	0.26***	0.37***	0.38***	0.42***	0.51***	0.48***
	(0.062)	(0.078)	(0.079)	(0.068)	(0.069)	(0.066)	(0.067)
$\tilde{q}_{ij,t-1}$	0.43**	−0.05	−0.06	−0.16	0.09	0.17	0.25
	(0.207)	(0.168)	(0.174)	(0.235)	(0.216)	(0.243)	(0.201)
$\widetilde{hc}_{ij,t-1}$	−0.03**	−0.02*	−0.01	−0.02*	−0.02*	−0.03***	−0.03***
	(0.013)	(0.014)	(0.014)	(0.012)	(0.012)	(0.012)	(0.012)
$\widetilde{\Delta p^l}$	0.21***	0.09**	0.11**	0.12***	0.12***	0.17***	0.17***
	(0.056)	(0.041)	(0.050)	(0.043)	(0.042)	(0.044)	(0.039)
ρ				0.76***	0.58***	0.31**	0.34***
				(0.110)	(0.107)	(0.147)	(0.127)
Instrument diagnostics							
Hansen J-statistic	23.2 (15)	41.4 (15)	46.9 (15)	51.9 (19)	40.1 (19)	27.3 (17)	27.5 (18)
p-value of J-stat. > 0.05	Passed	Failed	Failed	Failed	Failed	Passed	Passed
C-stat. for IV in *LEV*	8.2 (7)	24.5 (7)	19.0 (7)	23.4 (8)	17.1 (8)	18.6 (8)	10.7 (8)
p-value of C-stat. > 0.05	Passed	Failed	Failed	Failed	Failed	Failed	Passed

(*continued on the next page*)

Table 4.4 (Continued)

DPD model:	Aspatial	Spatial filtering		Spatial lag model			
Weights matrix:	None	Border	Distance	Border	Distance	Border	Distance
	I	II	III	IV	V	VI	VII
Residual based spatial independence tests							
$Z(I)_{1994}$	7.12***	−3.38***	−1.82**	−3.53***	0.08	2.02**	3.27***
$Z(I)_{1995}$	2.55***	−4.34***	−0.98	−4.00***	0.58	−1.36*	1.81**
$Z(I)_{1996}$	4.83***	−2.41***	−1.25	−1.77**	0.51	1.90**	2.13**
$Z(I)_{1997}$	2.32**	−2.84***	−1.53*	−2.92***	−0.72	−0.36	0.54
$Z(I)_{1998}$	5.67***	−3.75***	0.03	−3.23***	2.42***	1.31	5.03***
$Z(I)_{1999}$	5.15***	−3.25***	−3.05***	−2.13**	−0.19	1.29	1.84**
$Z(I)_{2000}$	12.67***	−0.61	0.88	−0.42	1.50*	6.97***	4.31***
$Z(I)_{2001}$	11.74***	−2.40***	−0.38	−1.43*	1.78**	5.30***	4.16***
$Z(I)_{2002}$	7.63***	−1.56*	−0.59	−1.78**	1.06	1.80**	3.05***
$Z(I)_{2003}$	7.14***	−2.83***	−2.87***	−1.51*	1.63*	2.05**	4.18***
$Z(I)_{2004}$	7.94***	−1.31*	−0.99	−1.45*	1.71**	2.72***	4.73***
$Z(I)_{2005}$	10.83***	−2.19**	−0.58	−0.19	6.24***	6.25***	10.39***
$Z(I)_{2006}$	8.00***	−1.98**	−2.51***	−0.13	1.56*	3.70***	4.19***
$Z(STMI_P(t))$	9.32***	−6.09***	−1.77*	−5.00**	0.98	5.27***	4.04***
Efficient Wald GMM	1145.4***	18.7***	7.3**	63.4***	11.1***	355.8***	213.3***
No. of obs.	3120	3120	3120	3120	3120	3120	3120

Note: Standard errors (in brackets) are based on Windmeijer's (2005) finite-sample correction. For the Wald GMM test we run an auxiliary regression on each two-step GMM residual as $u = \kappa W u + \epsilon$ and test for the significance of κ according to a Wald F-test with $H_0 : \kappa = 0$ in the spirit of Egger et al. (2005)
*Denote statistical significance at the 10% level **Denote statistical significance at the 5% level ***Denote statistical significance at the 1% level

tests, the reported J- and C-statistic based instrument diagnostic tests for the aspatial model in Table 4.4 already report the outcome of a downward testing approach to reduce the number of included instruments in such a way that both critical J- and C-statistic criteria are satisfied (with p-value for $J_{crit.} > 0.05$, $C_{crit.} > 0.05$).[10] As argued above, the C-statistic thereby tests the consistency of the subset of instruments in the level equation, while the J-statistics evaluates the whole IV set. In total, this gives us a model with 15 overidentifying restrictions, which are used as benchmark IV set for the spatially augmented regression specifications.

Yet, contrary to the IV diagnostic tests the results for tests of spatial dependence in the residuals ($I(t)$, $STMI_P(t)$ and Wald GMM test) clearly reject the null of spatial independence. The latter poor result for the aspatial model calls for an explicit account of the spatial dimension in our DPD model context. We start with the Getis spatial filtering approach and estimate the transformed model in (4.1) by SYS-GMM both on the grounds of a common border and optimal distance based weighting schemes in columns II and III of Table 4.4, respectively. The estimated regression coefficients show some significant changes relative to the aspatial specification. First, the estimated coefficient of the lagged endogenous variable is substantially reduced though still significant. On the contrary, the parameter for regional wage rate differentials turns out to be higher. However, if we calculate the implied long-run elasticity for this variable in Table 4.5 we see that due to the two opposed effect the long-run elasticity of regional real wage rate differentials with respect to net migration flows remains roughly in line with the aspatial benchmark for the spatial filtered specifications (see Table 4.5).

Interestingly, the effect of unemployment rate differentials though being still negative turns out statistically insignificant in the estimated models based on the Getis filtering approach. The results are broadly in line with recent findings for internal US migration rates reported in Chun (2008): Here the author finds that the magnitude of the unemployment rate coefficient drops significantly, when moving from an aspatial to a spatial filtered (origin constrained) migration model. One way to interpret this result is that unemployment rate differences in the aspatial model also capture the omitted variable effect of other relevant economic and social factors, which arise through network structures in migration flows (as for instance outlined in the competing destinations model). If we appropriately account for network effects, the variable loses predictive power. One likely example is the provision of cultural goods, which is typically negatively correlated with the unemployment rate, but may well be an alternative spatially heterogeneous attractor of migration flows—especially for highly educated prospective migrants.

Looking at the postestimation tests, the optimal distance based weighting matrix shows a much better performance compared to the common border specification.

[10] The applied downward testing approach thereby has two distinct features: First, we reduce the total number of IVs by using collapsed rather than uncollapsed instruments as suggested in Roodman (2009). Second, based on the collapsed IV specification we finally reduce the number of instruments using a C-statistic based algorithm, which is able to subsequently identify those IV subsets with the highest test results (see Mitze 2009, for details).

Table 4.5 Total effects ($\bar{M}(x)_{total,LR}$) for the explanatory regressors in the empirical migration model

Model:	Aspatial model	Spatial filtering	Spatial lag model
W^*:	None	Distance	Distance
	I	III	VII
$\widetilde{wr}_{total,LR}$	0.43	0.61	1.15
$\widetilde{ur}_{total,LR}$	−0.33	−0.14	−0.31
$\Delta\widetilde{ylr}_{total,LR}$	1.12	0.58	1.85
$\tilde{q}_{total,LR}$	0.88	−0.09	0.96
$\widetilde{hc}_{total,LR}$	−0.06	−0.02	−0.12
$\widetilde{\Delta p}^{l}_{total,LR}$	0.43	0.17	0.65

Note: Since the SAR model includes a spatial lag besides the time lag, the average total long-run effect $\bar{M}(x)_{total,LR}$ for each regressor x is calculated as $\bar{M}(x)_{total,LR} = n^{-1}\iota_n' S_x(W)\iota_n = (1-\alpha-\rho)^{-1}\beta_x$, where $S_x(W) = (I_n - \alpha - \rho W)^{-1}\beta_x$ and ι_n is a constant term vector of ones and I_n is an n-dimensional identity matrix for the number of observations. For details, see LeSage and Pace (2009)

For the spatial filtering approach in column III only some few years still show significant spatial autocorrelation patterns when applying Moran's I to the model's residuals, while the border based approach in column II is less effective. However, both filtered specifications do not pass the joint Moran's I test as well as fail to pass the standard J- and C-statistic based IV diagnostic tests based on the same set of IVs as the aspatial benchmark (the latter results are rather robust to changes in the IV set).

If we look at the estimation results of the dynamic spatial lag regression approach in columns IV and V, they are both qualitatively and quantitatively much in line with the spatial filtering approach. One advantage of the spatial regression compared to the spatial filtering approach is that we can additionally give an interpretation for the parameter estimate for the spatial lag variable (ρ): Here the positive coefficient sign hints at positive spatial autocorrelation effects in German migration flows, giving rise to spillover effects motivated by theories of intervening opportunities and competing destinations. With respect to the postestimation test for spatial autocorrelation in the residuals the results for the spatial lag model mirror the findings of the spatial filtering approach that the optimal distance weighting matrix is much better equipped to filter out spatial dependences from the model.

For the optimal distance based weighting scheme the spatial lag model even passes the $STMI_P$ criterion. However, again the models fail to pass the J- and C-statistic criterion based on the IV set of the aspatial benchmark augmented by IVs for the spatial lag variable.[11] In columns VI and VII we therefore reduce the number of instruments for the spatial lag variable (eliminating those values with the highest individual C-statistic). As column VII shows, we are able to reduce the number of

[11] Therefore the number of overidentifying restrictions increases from 15 to 19.

instruments so that both the J- and C-statistic criterion is passed. Yet, this also reduces the estimated coefficient for the spatial lag variable (ρ) and leads to a higher degree of remaining spatial autocorrelation in the model's residuals indicated by higher Moran's I values (both for each individual year as well as pooled in terms of $STMI_P$).

Regarding the economic interpretation of the spatially augmented models, the long-run total effects for the spatial lag model from column VII in Table 4.5 show that differences in the wage rate and regional labor productivity have a higher impact compared to the aspatial benchmark specification, when accounting for spatial dependencies in the model. The latter result in fact may hint at the potential role played by spatial spillover effects from other regressors besides the dependent variable. We thus test for the improvement in the empirical results if we estimate the unconstrained spatial Durbin model according to (4.17). The regression results are shown in Table 4.6. We only focus on weighting matrices derived from optimal distances. The results show that most of the spatial lags of the explanatory variables turn out to be significant: For instance, a rise in the unemployment rate differential in neighboring regions shows to have a positive effect on the region's net in-migration rate. The opposite holds for changes in labor productivity growth and the labor participation rate in neighboring regions.

We see that the spatial Durbin model in column VIII is also very successful in capturing spatial dependence in the migration equation. As first specification the model passes the joint Moran's I test for spatial autocorrelation over the full sample period as well as the GMM-based Wald test to detect spatially autocorrelation in the error terms. But again, given the large number of instruments employed, the model is not able to pass the IV diagnostic tests. If we reduce the number of instruments, we come back to the above problem that the model passes the J-test, but at the same time the performance in terms of capturing the existing spatial dependence in the model significantly worsens. Taken together, this may hint at a certain trade-off between IV consistency and effective spatial modelling for both the spatial filtering as well as spatial regression approaches (both the spatial lag as well as spatial Durbin model) in IV/GMM estimation.

Trying to circumvent this trade-off, as a final exercise we test for the impact on the empirical results if we combine the spatial filtering and spatial regression approach in the following way:

$$nm_{ij,t} = \alpha nm_{ij,t-1} + \rho \left(W \times nm_{ij,t}\right) + \sum_{k=0}^{K} \beta_k^{*\prime} X_{ij,t-k}^{*} + u_{ij,t}. \qquad (4.24)$$

We use unfiltered values for the endogenous variable and account for spatial autocorrelation in terms of the spatial lag variable $W_t Y_t$, moreover we use spatially filtered exogenous variables X^*. The empirical specification in columns XI and XII have the potential advantage that they reduce the number of instrument counts and multicollinearity among regressors since no spatial lags besides the dependent variable are included. If the researcher's primary interest is to get an interpretation of spatial spillovers from the parameter coefficient of the endogenous variable, while

Table 4.6 Estimation results for spatial Durbin model and a mixed spatial regression-filtering model

DPD model:	Spatial Durbin model			Mixed filt. & reg.	
Weights matrix:	Distance VIII	Distance IX	Distance X	Distance XI	Distance XII
$nm_{ij,t-1}$	0.31***	0.23***	0.20***	0.35***	0.20**
	(0.043)	(0.078)	(0.073)	(0.068)	(0.085)
$\widetilde{wr}_{ij,t-1}$	0.36*	0.22	−0.60	0.46***	0.68***
	(0.215)	(0.269)	(0.485)	(0.138)	(0.151)
$W \times \widetilde{wr}_{ij,t-1}$	0.16	0.28	1.24**		
	(0.283)	(0.348)	(0.641)		
$\widetilde{ur}_{ij,t-1}$	−0.31**	−0.16	−0.58***	−0.02	−0.01
	(0.123)	(0.140)	(0.195)	(0.061)	(0.054)
$W \times \widetilde{ur}_{ij,t-1}$	0.56***	0.31**	0.84***		
	(0.152)	(0.156)	(0.264)		
$\Delta\widetilde{ylr}_{ij,t-1}$	0.67***	0.70***	0.27*	0.37***	0.63***
	(0.129)	(0.137)	(0.145)	(0.099)	(0.108)
$W \times \Delta\widetilde{ylr}_{ij,t-1}$	−0.44***	−0.53***	0.11		
	(0.149)	(0.159)	(0.182)		
$\tilde{q}_{ij,t-1}$	0.46	0.95***	1.16**	−0.05	0.05
	(0.306)	(0.358)	(0.492)	(0.223)	(0.182)
$W \times \tilde{q}_{ij,t-1}$	−0.81***	−1.02***	−1.30***		
	(0.275)	(0.364)	(0.488)		
$\widetilde{hc}_{ij,t-1}$	−0.02	−0.06	−0.12***	−0.02	−0.01
	(0.038)	(0.041)	(0.041)	(0.014)	(0.026)
$W \times \widetilde{hc}_{ij,t-1}$	0.02	0.05	0.10**		
	(0.041)	(0.043)	(0.044)		
$\widetilde{\Delta p^l}$	−0.01	0.23*	1.29***	0.15***	0.18***
	(0.036)	(0.121)	(0.251)	(0.055)	(0.061)
$W \times \widetilde{\Delta p^l}$	0.04	−0.27	−2.13***		
	(0.062)	(0.196)	(0.418)		
ρ	0.80***	0.76***	0.80***	0.70***	0.79***
	(0.081)	(0.127)	(0.116)	(0.177)	(0.123)
Hansen J-statistic	121.6 (48)	71.2 (28)	32.3 (22)	61.6 (18)	25.8 (16)
p-value of J-stat. > 0.05	Failed	Failed	Passed	Failed	Passed
C-stat. for IV in *LEV*	25.8 (14)	26.5 (12)	17.5 (9)	27.3 (8)	4.1 (7)
p-value of C-stat. > 0.05	Failed	Failed	Failed	Failed	Passed

(*continued on the next page*)

Table 4.6 (Continued)

DPD model:	Spatial Durbin model			Mixed filt. & reg.	
Weights matrix:	Distance VIII	Distance IX	Distance X	Distance XI	Distance XII
$Z(I)_{1994}$	0.417	1.04	1.21	0.47	0.11
$Z(I)_{1995}$	0.33	1.22	1.26	0.02	1.17
$Z(I)_{1996}$	1.41^{*}	2.22^{**}	1.51^{*}	0.69	1.42^{*}
$Z(I)_{1997}$	−0.69	0.59	2.83^{***}	−0.44	0.67
$Z(I)_{1998}$	2.38^{***}	3.83^{***}	4.04^{***}	1.38^{*}	2.25^{**}
$Z(I)_{1999}$	−1.63	−0.23	0.91	-1.81^{**}	-1.61^{*}
$Z(I)_{2000}$	−0.54	0.67	5.03^{***}	0.13	−0.23
$Z(I)_{2001}$	0.58	1.41^{*}	2.88^{***}	−0.17	0.36
$Z(I)_{2002}$	−0.51	0.29	1.24	−0.95	−0.67
$Z(I)_{2003}$	−0.28	0.42	3.45^{***}	−0.37	1.38^{*}
$Z(I)_{2004}$	−1.11	−0.13	2.69^{***}	-1.73^{**}	−0.98
$Z(I)_{2005}$	1.52^{*}	3.01^{***}	8.31^{***}	1.66^{**}	1.34^{*}
$Z(I)_{2006}$	0.84	2.59^{***}	4.07^{***}	-1.96^{**}	-1.43^{*}
$Z(STMI_P(t))$	−0.26	1.02	3.27^{***}	1.91^{*}	−0.32
Efficient Wald GMM	2.4	15.8^{***}	123.2^{***}	12.8^{***}	2.2

*Denote statistical significance at the 10% level **Denote statistical significance at the 5% level
***Denote statistical significance at the 1% level

at the same time retain well-behaved residuals, this mixed filtering-regression approach may be a feasible estimation strategy.

Although the mixed model with the IV set from the benchmark specification first fails to pass the J- and C-statistic criteria it is remarkably good in terms of capturing spatial dependence in the structural parameters of the model. As the year specific Moran's I values show, only in very few year there some evidence of remaining spatial autocorrelation. Moreover, as it was the case for the spatial Durbin model, the mixed filtering-regression specification shows only weak evidence for remaining spatial autocorrelation based on the pooled space–time Moran's I statistic.

In column XII we are able to reduce the IV set in such a way that the model also passes the standard IV diagnostic tests for the given J- and C-statistic criteria. This improvement in the standard tests for instrument validity goes in line with a good performance in properly capturing spatial dependence: Only rarely the annual Moran's I identifies remaining spatial autocorrelation in the residuals, which is among the best empirical track record among all rival specification. The model also passes the $STMI_P(t)$ criterion as well as the GMM-based Wald test for spatial autocorrelation in the model's error term.

The only remaining flaw is that most augmented specifications in Table 4.6 either fail or are close to break the stability condition from (4.3) requiring $|\alpha + \rho| < 1$. Nevertheless, the mixed filtering-regression model from column XII performs better compared to model specifications with larger instrument sets as in column VIII, where the latter—although performing well in terms of capturing spatial dependence—faces severe problems with respect to the stability condition.

Summing up, the obtained regression results show that both time and space are important dimensions to account for in the empirical analysis. For the different specifications in the GMM framework, we observe a general trade-off between IV consistency and spatial independence of the residuals. As best alternative from the perspective of standard IV and spatial dependence diagnostic tests serves a mixed filtering-regression approach, which allows to quantify the effect of spillovers from spatially linked migration flows as well as shows a good postestimation testing results. However, further research effort should be devoted to a careful analysis of the dynamic properties of such systems.

4.5 Conclusion

In this paper, we have explored the potential role of spatial autocorrelation in the analysis of interregional migration flows for Germany since re-unification. Though there is a huge body of literature dealing with structural determinants of German internal migration, no extensive testing for the role of space–time dynamic processes has been conducted so far. Starting from a standard aspatial specification of the neoclassical migration model in a dynamic panel data context, we have shown that spatial autocorrelation is highly present. By means of an appropriate estimation strategy, which augments the standard Blundell–Bond (1998) system GMM estimator by spatial lags of the endogenous and explanatory variables, we have then applied the extended SYS-GMM to a spatial lag as well as an unconstrained spatial Durbin model approach. As an alternative approach we used spatial filtering techniques to remove spatial dependence embedded in the set of variables. In order to apply both spatial regression and filtering techniques we have construct a set of binary spatial weighting matrices (both based on common borders as well as optimal geographical distances derived from a threshold measure) for our migration flow data. The resulting spatial weighting framework is able to simultaneously capture both origin- as well destination related interaction effects.

The regression results show that the spatial models are able to remove a large part of spatial dependences from our model's residuals. In terms of the augmented SYS-GMM estimator, the spatial Durbin model shows the best performance in capturing spatial dependences among migration flows. However, since it employs a large number of instruments, we observe a trade-off between instrument consistency (measured by the Hansen J-statistic overidentification tests) and effective spatial modelling. Applying a mixed spatial filtering-regression approach to reduce the number of instrument counts circumvents this problem. The specification passes both standard IV diagnostic tests as well as tests for spatial independence of the residuals. The latter approach may give rise to further improvements in terms of consistent and efficient estimation strategies for dynamic spatial panel data models. It is in line with earlier findings such as in Elhorst et al. (2010), who propose a mixture of different (ML and GMM based) estimation techniques for complex models with space–time dynamics. Further research effort thus should especially focus on a thorough analysis of the dynamic properties and stability of such space–time specifications.

Appendix A: Space–Time Moran's I Indices

To formally define Space–Time Moran's I ($STMI$) indices we start from the standard Moran's I statistic defined as a standard indicator of spatial association between two neighboring observations i and j in period t for variable y and elements w of a spatial weighting matrix W according to (for notational convenience we use the standard 'entity based' notation here, however the extension to the dyadic/flow case is straightforward):

$$I(t) = \frac{N}{S_0} \frac{\sum_{i=1}^{N} \sum_{j=1}^{N} w_{ij}(y_{i,t} - \bar{y}_t)(y_{j,t} - \bar{y}_t)}{\sum_{i=1}^{N}(y_{i,t} - \bar{y}_t)^2} \tag{4.25}$$

where $S_0 = (\sum_{i=1}^{N} \sum_{j=1}^{N} w_{ij})$ is a measure of the overall connectivity of the geographical system and $\bar{y} = (\sum_{i=1}^{N} y_i/N)$. This measure captures the correlation between values for y and its spatial lag $W \times y$ for a specific time period t. A first step towards a space–time autocorrelation statistic is then to introduce a lag structure in the computation of Moran's I. As Lopez and Chasco (2007) point out, the resulting $STMI(t-k)$ computes the relationship between the spatial lag $W \times y_t$, at time t, and the original variable y, at time $(t-k)$, where k defines the order of the time lag. Hence, this statistic quantifies the influence that a change in a spatial variable y, which operated in the past $(t-k)$ in an individual location i, exerts over its neighborhood at present t. According to Griffith (1981) the time lag can formally be introduced as

$$STMI(t-k) = \frac{N}{S_0} \frac{\sum_{i=1}^{N} \sum_{j=1}^{N} w_{ij}(y_{i,t} - \bar{y}_t)(y_{j,t-k} - \bar{y}_t)}{\sum_{i=1}^{N}(y_{i,t} - \bar{y}_t)^2}. \tag{4.26}$$

For exploratory space–time data analysis (ESTDA) purposes, both I_t and $STMI(t-k)$ can be visualized in terms of Moran scatterplots, where the test statistic coincides with the slope of the regression line of $W \times y_t$ on y_{t-k} using variables in $N(0,1)$-standardized form. This allows for a graphical inspection of the spatial autocorrelation pattern present in the dataset. For increasing $k > 0$, additionally Moran space–time autocorrelation functions and surface plots can be computed. The latter may give a first indication about the presence and time persistence of space–time dependencies for a given variable. While Moran space–time autocorrelation functions plot the $STMI(t-k)$ for a given year t and increasing lag length k, Moran surface plots even allow to investigate the evolution of $STMI(t-k)$ for the whole period of time.

For the case of panel data, singular statistics of spatial association for each period of time—as defined above—may nevertheless be inefficient relative to their 'pooled' counterparts. Thus, aggregating over the time dimension results in the pooled $STMI_P(t-k)$ measure as

$$STMI_P(t-k) = \frac{(T-k)N}{S_1} \frac{\sum_{t=1+k}^{T} \sum_{i=1}^{N} \sum_{j=1}^{N} \vartheta_{ij,t-k}(y_{i,t}-\bar{y})(y_{j,t-k}-\bar{y}_t)}{\sum_{t=1}^{T} \sum_{i=1}^{N} (y_{i,t}-\bar{y})^2}, \tag{4.27}$$

where $S_1 = (\sum_{t=1+k}^{T} \sum_{i=1}^{N} \sum_{j=1}^{N} \vartheta_{ij,t-k})$ and $\bar{y} = (\sum_{t=1}^{T} \sum_{i=1}^{N} y_{i,t}/NT)$. In extension to the elements w_{ij} of a standard weighting matrix W_N of dimension $N \times N$, $\vartheta_{ij,t}$ are elements of an extended spatial weighting matrix W_{NT} of dimension $NT \times NT$ taking values

$$\vartheta_{ij,t} = \begin{cases} 1 & \text{if } i \text{ and } j \text{ are neighborhood observations during time period } t-k, \\ 0 & \text{otherwise.} \end{cases} \tag{4.28}$$

For $k = 0$, $STMI_P$ is a straightforward extension to Moran's I from (4.25), where the matrix elements $\vartheta_{ij,t}$ represent a stacked weighting matrix according to (4.23) or—for identical W_t over time—can be calculated as $W_t \otimes I_T$. For $k > 0$ the structure of the temporal dependence can easily be extended by replacing the zero matrix entries under and above the main diagonal in I_T by values of 'one'. To conduct statistical inference based on $STMI_P(t-k)$ we finally need to derive its first and second moments. Here we follow Griffith (1981) and write the mean of the sampling distribution as

$$E(STMI_P(t-k)) = -\frac{(T-k)}{T(NT-k)}, \tag{4.29}$$

and the second moment as

$$\begin{aligned} &E(STMI_P^2(t-k)) \\ &\quad = \frac{(T-k)^2}{T^2(NT-k)(NT+k)(\sum_{t=1+k}^{T} \sum_{i=1}^{N} \sum_{j=1}^{N} c_{ij,t-k})^2} \\ &\qquad \times \left[2N^2T^2 \sum_{t=1+k}^{T} \sum_{i=1}^{N} \sum_{j=1}^{N} {c_{ij,t-k}}^2 - 4NT \sum_{i=1}^{N} \left(\sum_{t=1+k}^{T} \sum_{j=1}^{N} c_{ij,t-k} \right)^2 \right. \\ &\qquad \left. + 3 \left(\sum_{t=1+k}^{T} \sum_{i=1}^{N} \sum_{j=1}^{N} c_{ij,t-k} \right)^2 \right]. \end{aligned} \tag{4.30}$$

The standard error of the sampling distribution of $STMI_P(t-k)$ may be determined by combining (4.29) and (4.30) such that

$$\sigma_{STMI_P(t-k)} = \left(E(STMI_P^2(t-k)) - [E(STMI_P(t-k))]^2\right)^{1/2}. \tag{4.31}$$

Under the assumption of normality for reasonably large N and T the test statistics then becomes

$$Z = \frac{STMI_P(t-k) + E(STMI_P(t-k))}{\sigma_{STMI_P(t-k)}}. \tag{4.32}$$

Appendix B: Spatial Filtering and Optimal Distance Based Weight Matrix

Similar to the idea of filtering seasonality out of time series data spatial filtering techniques convert variables that are spatially autocorrelated into spatially independent variables and a residual—purely spatial—component. Among the commonly applied spatial filtering techniques is the Getis (1990, 1995) as well as the Griffith (1996, 2003) eigenvector spatial filtering approach. A recent empirical comparison of both filtering techniques has shown that both approaches are almost equally equipped for removing spatial effects from geographically organized variables (see e.g. Getis and Griffith 2002). For the remainder of the paper we rely on the Getis approach, which has been applied in variety of empirical research contexts (see e.g. Badinger and Url 1999; Badinger et al. 2004; Battisti and Di Vaio 2008, and Mayor and Lopez 2008). The idea of the spatial filtering approach is based on the consideration of a spatial vector S:

$$S \approx \rho W Y, \tag{4.33}$$

which takes the place of both the spatial weights matrix W and the spatial lag coefficient ρ for variable Y and allows the conversion of the dependent variable into its non-spatial equivalence as $Y^* = (Y - S)$. Once the filtering exercise has computed a set of non-spatial variables the second step regression task can be performed under the independence assumption yielding unbiased estimation results for the underlying model. To derive the set of spatially filtered variables the Getis approach uses the local statistic $G_i(d)$ by Getis and Ord (1992) defined as (in standard 'entity based' notation, the extension to dyadic/flow data can be done without loss of generality):

$$G_i(d) = \frac{\sum_{j=1}^N w_{ij}(d) y_j}{\sum_{j=1}^N y_j}, \quad \text{with } i \neq j. \tag{4.34}$$

The $G_i(d)$-statistic calculates the ratio between the sum of the y_j values included within a distance d from region i and the sum of the values in all the regions excluding i. It thus measures the concentration of the sum of values in the considered area and would increase their result when high values of variable y are found within a distance d from i. For empirical application one has to note that the use of this approach is limited by the nature of the $G_i(d)$-statistic which requires all variables to have a natural origin and be positive. Moreover, the matrix of spatial weights has to be binary (not row-standardized). The first and second moments are given by:

$$E(G_i(d)) = \frac{\sum_{j=1}^{N} w_{ij}(d)}{(N-1)} = \frac{W_i}{(N-1)}, \tag{4.35}$$

$$\mathrm{Var}(G_i(d)) = \frac{W_i(N-1-W_i)}{(N-1)^2(n-2)} \left(\frac{F_{i2}}{F_{i1}^2}\right), \tag{4.36}$$

where

$$F_{i1} = \frac{\sum_j y_j}{N-1} \quad \text{and} \quad F_{i2} = \frac{\sum_{j=1} y_j^2}{N-1} - F_{i1}^2. \tag{4.37}$$

Assuming a normal distribution we can finally derive the test statistic $Z(G)_i$ from the above expressions as:[12]

$$Z(G)_i = \frac{G_i(d) - E[G_i(d)]}{\sqrt{\mathrm{Var}(G_i(d))}}. \tag{4.38}$$

According to Getis (1995) the filtered variables can then be computed from the $G_i(d)$-statistic in the following way: Since its expected value $E[G_i(d)]$ represents the value in location i when the spatial autocorrelation is absent, the ratio $G_i(d)/E[G_i(d)]$ is used in order to remove the spatial dependence included in the variable. The spatially uncorrelated component of variable y can then be derived as

$$y_i^* = \frac{y_i \times (\frac{W_i}{N-1})}{G_i(d)}. \tag{4.39}$$

The difference between the original y and the filtered variable y^* is a new variable $\ddot{y} = (y - y^*)$ that represents purely spatial effects embedded in y.

As Badinger and Url (1999) point out, the choice of an appropriate distance d is essential for filtering. The optimal distance can thereby be interpreted as the radius of an area where spatial effects maximize the probability of deviations between observations and expected values. One option to set up this radius is in terms of border regions. Alternatively, using geographical distance between regions, Getis (1995) suggests to choose the d-value which maximizes the absolute sum of the normal standard variate of the $G_i(d)$-statistic:

$$\max \sum_{i=1}^{N} |Z(G)_i| = \max \sum_{i=1}^{N} \frac{|G_i(d) - E[G_i(d)]|}{\sqrt{\mathrm{Var}(G_i(d)}}. \tag{4.40}$$

[12]The underlying null hypothesis of $Z(G)_i$ states that the values within a distance d from i are a random sample drawn without replacement from the set of all possible values.

Table 4.7 Z-statistic of Moran's I values for the Getis (1995) spatially filtered variables

Year	Border	Optimal distance				
	nm^*_{ij}	nm^*_{ij}	wr^*_i	ur^*_i	yrl^*_i	hc^*_i
1991	0.66	0.07	−1.05	−1.07	−2.05**	−0.91
1992	−0.84	−0.94	−1.21	−1.11	−1.76**	−0.86
1993	−1.90**	0.12	−1.39*	−1.12	−1.35*	−0.89
1994	−3.23***	−1.44*	−1.41*	−1.07	−0.89	−0.89
1995	−3.38***	0.98	−1.46*	−1.05	−0.65	−0.93
1996	−2.73***	−0.70	−1.43*	−0.98	−0.43	−0.87
1997	−2.83***	−0.74	−1.37*	−0.90	−0.30	−0.74
1998	−2.65***	1.25	−1.38*	−0.73	−0.26	−0.97
1999	−1.65**	−0.94	−1.36*	−0.66	−0.06	0.63
2000	0.04	0.83	−1.29*	−0.65	−0.04	−1.21
2001	−0.10	1.43*	−1.28*	−0.59	−0.16	−0.92
2002	−0.09	1.42*	−1.28*	−0.58	−0.13	−0.86
2003	−1.18	0.22	−1.27	−0.71	0.02	−0.86
2004	−1.13	0.08	−1.23	−0.76	0.12	−0.78
2005	−2.02**	0.05	−1.25	−0.65	−0.01	−0.55
2006	−0.27	−1.07	−1.26	−0.63	−0.02	−0.83

Note: For both endogenous and exogenous variables we use information in levels and the exogenous variables are filtered in their original form. The optimal distance values are: $wr = 300$ km, $ur = 400$ km, $yrl = 225$ km, $q = 225$ km, $hc = 450$ km, $p^l = 350$ km and kept constant over the sample periods. A sensitivity analysis with time-varying d-values did not change the results significantly. We do not report filtering results for q and Δp^{l*} since those variable do not show significant autocorrelation effects

*Denote statistical significance at the 10% level **Denote statistical significance at the 5% level

***Denote statistical significance at the 1% level

As a first indication of the appropriateness of the Getis filtering approach, Table 4.7 reports the results of the Moran's I test statistics applied to the filtered variables (except those being tested spatially independent, namely $\tilde{q}$ and $\Delta\tilde{p}^l$). As the table shows for the dependent variable (nm^*) the optimal distance based weighting scheme is much more successful in eliminating spatial dependences compared to the border based alternative. Distance between two states is thereby calculated as the road distance in kilometers between a population weighted average of major city pairs for each pair of regions. Details of the cities included in the sample and the resulting distance matrix are given in Tables 4.8 and 4.9 respectively.

Table 4.8 Major cities among German states based on population levels in 2006

No.	Rank	City	Pop. in 2006	Pop. weight	State
1	1	Stuttgart	593923	0.389	Baden-Württemberg
2	2	Mannheim	307914	0.202	Baden-Württemberg
3	3	Karlsruhe	286327	0.188	Baden-Württemberg
4	4	Freiburg	217547	0.143	Baden-Württemberg
5	5	Ulm	120925	0.079	Baden-Württemberg
6	1	München	1294608	0.557	Bavaria
7	2	Nürnberg	500855	0.215	Bavaria
8	3	Augsburg	262512	0.113	Bavaria
9	4	Würzburg	134913	0.058	Bavaria
10	5	Regensburg	131342	0.057	Bavaria
11	1	Berlin	3404037	1.000	Berlin
12	1	Potsdam	148813	0.472	Brandenburg
13	2	Cottbus	103837	0.329	Brandenburg
14	3	Frankfurt/Oder	62594	0.199	Brandenburg
15	1	Bremen	547934	1.000	Bremen
16	1	Frankfurt/Main	652610	0.550	Hessen
17	2	Wiesbaden	275562	0.232	Hessen
18	3	Kassel	193518	0.163	Hessen
19	4	Fulda	63916	0.055	Hessen
20	1	Hamburg	1754182	1.000	Hamburg
21	1	Rostock	199868	0.550	Mecklenburg-Vorpommern
22	2	Schwerin	96280	0.265	Mecklenburg-Vorpommern
23	3	Neubrandenburg	67517	0.186	Mecklenburg-Vorpommern
24	1	Hannover	516343	0.512	Lower Saxony
25	2	Braunschweig	245467	0.244	Lower Saxony
26	3	Osnabrück	163020	0.162	Lower Saxony
27	4	Wilhelmshaven	82797	0.082	Lower Saxony
28	1	Köln	989766	0.368	North Rhine-Westphalia
29	2	Dortmund	587624	0.218	North Rhine-Westphalia
30	3	Essen	583198	0.217	North Rhine-Westphalia
31	4	Münster	272106	0.101	North Rhine-Westphalia
32	5	Aachen	258770	0.096	North Rhine-Westphalia
33	1	Mainz	196425	0.345	Rhineland-Palatine
34	2	Ludwigshafen	163560	0.287	Rhineland-Palatine
35	3	Koblenz	105888	0.186	Rhineland-Palatine
36	4	Trier	103518	0.182	Rhineland-Palatine
37	1	Saarbrücken	177870	1.000	Saarland
38	1	Leipzig	506578	0.403	Saxony
39	2	Dresden	504795	0.402	Saxony
40	3	Chemnitz	245700	0.195	Saxony
41	1	Halle (Saale)	235720	0.506	Saxony-Anhalt
42	2	Magdeburg	229826	0.494	Saxony-Anhalt
43	1	Kiel	235366	0.527	Schleswig-Holstein
44	2	Lübeck	211213	0.473	Schleswig-Holstein
45	1	Erfurt	202658	0.497	Thuringia
46	2	Gera	102733	0.252	Thuringia
47	3	Jena	102494	0.251	Thuringia

Table 4.9 Distance matrix for German states based on population weighted inter-city connections in road kilometers

	BW	BAY	BER	BRA	BRE	HH	HES	MV	NIE	NRW	RHP	SAAR	SACH	ST	SH	TH
BW	0															
BAY	262	0														
BER	672	523	0													
BRA	673	518	88	0												
BRE	633	650	375	440	0											
HH	667	666	279	364	110	0										
HES	231	308	527	556	424	473	0									
MV	802	701	207	291	278	152	596	0								
NIE	529	541	295	351	130	177	310	345	0							
NRW	410	501	521	584	273	363	234	555	265	0						
RHP	207	339	619	639	483	553	163	715	427	251	0					
SAAR	226	378	745	758	590	690	255	847	544	349	146	0				
SACH	579	461	210	202	431	450	388	398	417	534	505	615	0			
ST	549	416	150	200	295	317	351	316	261	416	497	592	206	0		
SH	732	745	316	398	192	76	510	181	272	447	629	754	523	396	0	
TH	440	317	269	293	391	418	247	433	359	411	369	471	145	163	487	0

Note: For further details about included cities see Table 4.8. Inter-city distances in road kilometers calculated with the help of www.map24.de

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Part II
Trade and FDI Activity

Chapter 5
Trade-FDI Linkages in a Simultaneous Equations System of Gravity Models for German Regional Data

5.1 Introduction

We use a system of simultaneous gravity equations to model German (regional) trade and FDI patterns within the EU27 and to explore correlations among these variables. Whereas predictions from standard trade models of the Heckscher–Ohlin type typically handle both variables as substitutes, recent theoretical contributions in the field of New Trade Theory (NTT) show a more diverse picture when accounting for the growing complexity of investment strategies by multinational enterprises (MNEs), which may follow either horizontal (market-seeking) and/or vertical (cost oriented) investment motives. Depending on the mixture of these two modes, both substitutive and complementary linkages could potentially arise, crucially depending on the chosen model assumptions.[1] Adding on the theoretical literature in solving the trade-FDI puzzle, there is also a steadily increasing stock of empirical contributions, which aim to gain insights to the trade-FDI relationships for individual countries or country groups. Though there is a general tendency for complementary linkages, the empirical literature also gives merely heterogeneous answers to this question. According to Aizenman and Noy (2006), an important aspect to account for in empirical work is to closely interpret the estimation result in light of the chosen country, industry sample and time period.

The research effort spent on solving the trade-FDI puzzle reflects the interest on this subject in the policy debate. As Pantulu and Poon (2003) point out, trade sub-

[1] Markusen (1995), Jungmittag (1995), Zarotiadis and Mylonidis (2005), Helpman (2006) and Blanchard et al. (2008) among others provide detailed surveys of recent theoretical contributions.

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Jointly with Björn Alecke and Gerhard Untiedt. Björn Alecke, Gesellschaft für Finanz- und Regionalanalysen (GEFRA), e-mail: Alecke@gefra-muenster.de; Gerhard Untiedt, GEFRA & Technical University Clausthal, e-mail: Untiedt@gefra-muenster.de.

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stitutability and replacement effects are sensitive issues in the globalization debate of industrialized countries, linking outward FDI typically to deindustrialization and displacement effects of employment, especially in export-based industries. Thus, for relatively open economies like Germany this analysis may be seen as a very sensitive and important issue. Only few empirical studies have dealt with the German trade-FDI interrelations so far, where the results generally show a substitutive relationship between exports and outward FDI at the national level (see Jungmittag 1995, for selected European countries and the USA between 1973–89 as well as Egger and Pfaffermayr 2004, for a world sample between 1989–99). Accounting for the different historical patterns of unified Germany, an in-depth study of macro-regional differences between East and West Germany may also add a useful new dimension to the trade-FDI debate. This may answer the question in how far political and economic path dependencies in building up trade relations and foreign direct investment stocks may influence the actual internationalization strategies of firms.

To shed more light on the national and regional trade-FDI puzzle, we thus analyze the intra-EU27 trade and FDI patterns for the 16 German federal states (NUTS1-level) based on a panel data set of bilateral region-to-nation trade volumes and FDI stocks between 1993 and 2005.[2] We apply gravity type models in order to identify the driving forces of trade and FDI activity as proposed by the NTT and to gain insight into the likely nature of their interrelation. Econometrically, we estimate both instrumental variable (IV) and non-IV simultaneous equation models accounting for a likely correlation among the individual behavioral equations for trade and FDI. This strategy allows us to identify the underlying nature of the trade-FDI-nexus for Germany by isolating the pairwise effects of trade and FDI on the respective other variable, when controlling for a set of common external factors. Moreover, given the emphasis on the regional modelling perspective, we also put a special focus on a sensitivity analysis of the results with respect to the West and East German macro regions for different EU sub-aggregates.

The remainder of the chapter is organized as follows: Sect. 5.2 sketches the theoretical underpinnings of gravity type model of trade and FDI and also discusses its empirical operationalization. Section 5.3 gives a short literature review with respect to recent theoretical and empirical contributions to analyze trade-FDI-linkages in an international context. Section 5.4 then presents the database and some stylized facts for German trade and FDI patterns within the EU27. Section 5.5 then discusses the time series properties of the variables, the choice of the econometric estimator and our empirical results. Further, robustness checks are performed. Based on our empirical identification strategy, Sect. 5.6 reports the results for the trade-FDI linkages of the German aggregate and regional data. Section 5.7 concludes the chapter.

[2]It would be desirable to have region-to-region trade/FDI data between Germany and the EU27 economies. Unfortunately no such records are available.

5.2 Gravity Models of Trade and FDI

5.2.1 Theoretical Foundations

Given its empirical flexibility to model factor flows between regional and national entities in space, the gravity model has a long tradition in the field of international economics (see e.g. Matyas 1997; Feenstra 2004, for a recent overview). The empirical success of the model may be best explained by two facts: It is easy to apply empirically and its results are remarkably good. Starting as a rather ad-hoc empirical specification in the pioneering work of Tinbergen (1962) and Pöyhönen (1963), different scholars have also shown that the model can be derived consistently from theoretical trade models. Whereas earlier work particularly focused on export and import relationships, recent approaches have also adapted the framework to model FDI flow/stock movements motivated by common time features of trade and FDI (see e.g. Brenton et al. 1999). This section is intended to give a short sketch of the model's theoretical foundation and empirical operationalization.

In its fairly simple specification the standard gravity approach models trade between two countries as proportional to the (economic) mass of the countries (typically measured by GDP and population) and inversely related to the distance between them, adopting Newton's law for gravitational forces GF as

$$GF_{ij} = \frac{M_i M_j}{D_{ij}} \quad \text{for } i \neq j, \tag{5.1}$$

where $M_{i(j)}$ are the masses of two objects i and j, and D_{ij} is the distance between them. While the first variables proxy supply and demand conditions at home and abroad, the latter serves to measure obstacles to trade. The basic model can be augmented by several other variables and Lamotte (2002) argues that the choice of variables constitutes an important and delicate point, which has to be guided by theoretical and statistical concerns. Looking at its theoretical foundations, the gravity model can arise from a potentially large class of underlying economic structures. Anderson (1979), Helpman (1987) and Bergstrand (1985, 1989) were among the first to show that the gravity model can indeed be derived from a theoretical model. In the trade literature gravity type models based on classical Ricardian models, Heckscher–Ohlin models (see (Deardorff 1998)) and increasing returns to scale models of the NTT have been presented since then. As Henderson and Millimet (2008) summarize, though being different in structure, the models typically have the following common elements: 1) trade separability, which arises when local production and consumption decisions are separable from bilateral trade decisions among locations, 2) the aggregator of differentiated products is identical across locations and is of the constant elasticity of substitution form and 3) trade costs are invariant to trade volumes.

Based on these assumptions and considering a one-sector economy, where consumers have a common elasticity of substitution σ among all goods as well as symmetric transportation costs among trading partners, Anderson and van Wincoop (2003) derive a theory consistent gravity model equation as

$$Y_{ij} = \frac{X_i X_j}{X_w} \left(\frac{T_{ij}}{P_i P_j} \right)^{1-\sigma} \quad \text{or:} \quad Y_{ij} = k X_i X_j T_{ij}^{1-\sigma} P_i^{\sigma-1} P_j^{\sigma-1}, \tag{5.2}$$

where $k = 1/X_w$. Y_{ij} is the nominal value of exports from country i to j, $X_{i(j)}$ denotes total income for $i(j)$, X_w is world income, $(T_{ij} - 1)$ reflect 'iceberg' transportation (trade) costs and $P_{i(j)}$ are further (multilateral) resistance variables as described by Anderson and van Wincoop (2003).[3] Iceberg transportation costs indicate that T_{ij} units of the product must be shipped to country j in order for one unit to arrive. Feenstra (2004) proposes to model trade costs T_{ij} as a function of distance d_{ij} and other border effects associated with selling from country i to j. A similar specification can be used for modelling FDI.

5.2.2 *Empirical Operationalization*

We use the gravity model to specify a system of gravity equations for trade and FDI. Here, we have to decide whether to pool the data or use a cross-sectional specification and whether to estimate the gravity model from (5.2) in a log-linearized form. For a detailed discussion of the former point see e.g. Egger (2000), who points out several advantages of the panel data approach.[4] A discussion of the proper functional form in terms of a (log-)linear or non-linear specification is given in Coe and Tamirisa (2002), Henderson and Millimet (2008), as well as Santos Silva and Tenreyro (2006). The latter authors point to the fact that results may be misleading in the presence of heteroscedastic error terms. Since we are dealing with regional data, a correlation of cross-sections may indeed be a potential source of heteroscedasticity. To account for this, we follow Sarafidis and Robertson (2009) and include a set of time dummies, which should at least capture the homogeneous impact of cross-sections to unobserved common factors as one source of heteroscedastic errors. Additionally, Henderson and Millimet (2008) give strong evidence that concerns in the gravity literature over functional form appear unwarranted and that log-linear specifications offer reliable model predictions.[5]

Given the advantages of a panel specification over the cross-section approach, we operationalize the gravity model from (5.2) in line with Cheng and Wall (2002),

[3]In a multi-country framework X_w is defined as $X_w = \sum_{i=1}^{C} X_i$ with $i, j = 1, \ldots, C$ countries.

[4]First, a panel specification catches unobserved heterogeneity in the data caused by time-invariant individual effects (cross-section specific). Second, it allows capturing the relationships between the relevant variables over a longer period and hence is able to identify the role of the overall business cycle phenomenon. Moreover, given the unobserved nature of P_i and P_j in (5.2) a panel data model proxying these effects (for region i and j and/or an interaction term of the form $i \times j$) may thus be a promising alternative to an modelling strategy that tries to directly calculate these resistance variables (see Feenstra 2004, for an overview of different modelling strategies).

[5]The argument raised in Coe and Tamirisa (2002) relates to the problem of missing data due to log-linearization. We take up this point when discussing the data in Sect. 5.4.

Serlenga and Shin (2007) or Egger and Pfaffermayr (2004) in a log-linear way as:[6]

$$y_{ijt} = \alpha + \beta' \mathbf{x}_{ijt} + \gamma' \mathbf{z}_{ij} + u_{ijt} \quad \text{with } u_{ijt} = \mu_{ij} + \nu_{ijt}. \tag{5.3}$$

Here, y_{ijt} represents country i's internationalization activity with respect to country j for time period t (either trade or FDI), with $i = 1, 2, \ldots, N$; $j = 1, 2, \ldots, M$ and $t = 1, 2, \ldots, T$.[7] With regard to the explanatory regressors, $\mathbf{x}_{ijt}$ is a variable vector with variations in three dimensions (home country, host country and time $[x_{ijt}]$), with variation only in time and home country $[x_{it}]$ or time and foreign country $[x_{jt}]$ respectively. Analogously, $\mathbf{z}_{ij}$ is a variable vector of time fixed regressors. β and γ are vectors of regression coefficients, α is the overall constant term and u_{ijt} is the composite error term including the unobservable individual effects μ_{ij} (country pair or individual country/region effects) and a remainder error term ν_{ijt}. Typically, the latter two are assumed to be i.i.d. residuals with zero mean and constant variance.

We use a broad set of exogenous control variables in both $\mathbf{x}_{ijt}$ and $\mathbf{z}_{ij}$ to account for any simultaneity bias which arise because of a spurious correlation between trade and FDI when there are common exogenous factors that are affecting both these variables. This allows us to properly isolating the effect of trade and FDI measures on the respective other variables. A common way to run such a identification strategy is to specify the trade and FDI equations and then use the estimation residuals to run a regression as $\lambda_{ijt} = f(\phi_{ijt})$, where λ_{ijt} is the residual of the FDI regression (with ij denoting bilateral interaction between country i and j, t is the time index) and ϕ_{ijt} is the residual of the trade regression (or vice versa). Any significant positive or negative variable coefficient can then be interpreted in favor of non-zero trade-FDI linkages.[8]

Thus, using a log-linear form and variable selection based on both theoretical and statistical concerns, our resulting estimation system can be summarized as follows

$$\begin{aligned}
\log(EX_{ijt}) = \alpha_0 + \alpha_1 &+ \alpha_2 \log(GDP_{jt}) + \alpha_3 \log(POP_{it}) \\
&+ \alpha_4 \log(POP_{jt}) + \alpha_5 \log(PROD_{it}) + \alpha_6 \log(DIST_{ij}) \\
&+ \alpha_7 SIM + \alpha_8 RLF + \alpha_9 EMU \\
&+ \alpha_{10} EAST + \alpha_{11} BORDER + \alpha_{12} CEEC + \sum_{r=1993}^{2005} \alpha_r t_r,
\end{aligned} \tag{5.4}$$

$$\begin{aligned}
\log(FDIout_{ijt}) = \beta_0 &+ \beta_1 \log(GDP_{it}) + \beta_2 \log(GPD_{jt}) + \beta_3 \log(POP_{it}) \\
&+ \beta_4 \log(POP_{jt}) + \beta_5 \log(PROD_{it}) + \beta_6 \log(DIST_{ij})
\end{aligned}$$

---

[6] In running the empirical regressions, we also tested for alternative specification and evaluated them in terms of variable significance and post estimation model testing.

[7] Throughout the analysis, i identifies German states, while j represents the EU27 trading partner countries.

[8] Among the earlier contributions to this two-step approach determining trade-FDI linkages are Graham (1999) and Graham and Liu (1998), as well Brenton et al. (1999).

$$
\begin{aligned}
&+ \beta_7 \log(WAGE_{jt}) + \beta_8 \log(FDIopen_{jt}) + \beta_9 \log(K_{jt}) \\
&+ \beta_{10} SIM + \beta_{11} RLF + \beta_{12} EMU \\
&+ \beta_{13} EAST + \beta_{14} BORDER + \beta_{15} CEEC + \sum_{r=1993}^{2005} \beta_r t_r, \qquad (5.5)
\end{aligned}
$$

$$
\begin{aligned}
\log(IM_{ijt}) = {} & \gamma_0 + \gamma_1 \log(GDP_{it}) + \gamma_2 \log(GDP_{jt}) + \gamma_3 \log(POP_{it}) \\
&+ \gamma_4 \log(POP_{jt}) + \gamma_5 \log(PROD_{jt}) + \gamma_6 \log(DIST_{ij}) \\
&+ \gamma_7 SIM + \gamma_8 RLF + \gamma_9 EMU \\
&+ \gamma_{10} EAST + \gamma_{11} BORDER + \gamma_{12} CEEC + \sum_{r=1993}^{2005} \gamma_r t_r, \qquad (5.6)
\end{aligned}
$$

$$
\begin{aligned}
\log(FDIin_{ijt}) = {} & \delta_0 + \delta_1 \log(GDP_{it}) + \delta_2 \log(GDP_{jt}) + \delta_3 \log(POP_{it}) \\
&+ \delta_4 \log(POP_{jt}) + \delta_5 \log(PROD_{jt}) + \delta_6 \log(DIST_{ij}) \\
&+ \delta_7 \log(KI_{it}) + \delta_8 SIM + \delta_9 RLF + \delta_{10} EMU \\
&+ \delta_{11} EAST + \delta_{12} BORDER + \delta_{13} CEEC + \sum_{r=1993}^{2005} \delta_r t_r. \qquad (5.7)
\end{aligned}
$$

The dependent variable EX_{ijt} in (5.4) represents country i's exports to country j for time period t with an analogous notation for outward FDI ($FDIout_{ijt}$) in (5.5). The sub-indices for imports (IM_{ijt}) and inward FDI ($FDIin_{ijt}$) in (5.6) and (5.7) respectively, denote trade/FDI activity to i from j in period t. The use of time effects t_r is motivated by findings in Baldwin and Taglioni (2006). The authors show that an exclusion of such time effects may result in significant misspecifications, given the fact that it is often impossible to obtain trade- or FDI-specific price data. Moreover, time effects allow us controlling for business cycle effects over the sample period. The other variables are defined as follows:

- GDP = Gross domestic product in i and j respectively
- POP = Population in i and j
- $PROD$ = Labor productivity in i and j
- $DIST$ = Geographical distance between state/national capitals
- SIM = Similarity index defined as: $\log(1 - (\frac{GDP_{i,t}}{GDP_{i,t}+GDP_{j,t}})^2 - (\frac{GDP_{j,t}}{GDP_{i,t}+GDP_{j,t}})^2)$
- RLF = Relative factor endowments in i and j defined as: $\log|(\frac{GDP_{i,t}}{POP_{i,t}}) - (\frac{GDP_{j,t}}{POP_{j,t}})|$
- $WAGE$ = Wage compensation per employee in i and j
- $FDIopen$ = FDI openness in j as share of total inward FDI relative to GDP
- K = Total capital stock in i and j
- KI = Capital Intensity defined as Capital Stock per population in i
- EMU = EMU membership dummy for i and j
- $EAST$ = East German state dummy for i
- $BORDER$ = Border region dummy between i and j
- $CEEC$ = Central and Eastern European country dummy for j

We can classify the set of control variables as either being time-varying or time-fixed. Time varying explanatory variables for the trade equations (both import & export flows) used throughout this analysis include *GDP* for home region and foreign country, population at home and abroad (*POP*), as well as variables, measuring the relative share of inter-industry trade (or vertical vs. horizontal FDI, respectively) based on indices of the similarity of economic size (*SIM*) and relative factor endowments (*RLF*).[9] The variable *SIM* captures the relative size of two countries in terms of *GDP*, assuming that we can model each German state as an individual small open economy (SOE). The variable takes values between zero (absolute divergence) and 0.5 (equal country size). *RLF* captures differences in terms of relative factor endowments, where we assume that these endowments are closely linked to per-capita GDP as a proxy for the former. The *RLF* variable takes a minimum of zero for equal factor endowments in the two regions. Based on recent findings in NTT models, we also test the effect of home and host country labor productivity (defined as GDP per total employment) on trade. We finally specify a (one) time-varying dummy to check for trade/FDI-creating effects of the EMU starting from 1999.

The economic interpretation of the time-varying variables is as follows: For the export equation (and imports vice versa) GDP levels at home and abroad are expected to be positively correlated with the level of exports (imports) reflecting the theoretical argument that the supply and demand for differentiated varieties increases with absolute higher income values. A similar connection can also be established if we substitute absolute income levels by per capita GDP in i and j as a proxy for welfare levels. The effect of population is not that clear cut. The most prominent interpretation is offered by Baldwin (1994) that both home and foreign country population levels are negatively related to trade, since larger countries tend to be more self-sufficient in terms of production and resource endowment. An alternative interpretation is that a positive impact of exporter population on trade indicates labor intensive good exports, while a negative one stands for capital intensive export dominance (see e.g. Serlenga and Shin 2007). In this line of argumentation, a positive correlation of foreign population and trade may indicate exports in necessity goods (likewise a negative one for luxury goods). Next to GDP or GDP per capita level we may also consider productivity measures at home and abroad. With respect to home (foreign) country productivity, we expect a positive influence on exports (imports) inspired by recent theoretical findings that more productive firms on average tend to have a higher degree of internationalization. *SIM* may serve as an indicator for the relative share of intra-industry trade. That is, the more similar countries are in terms of GDP, the higher will be the share of intra-industry trade. The interpretation of *RLF* is in similar veins (but of opposite coefficient sign). For increasing differences in factor endowments, we expect a rise in the relative share of inter-industry trade. For the EMU dummy we expect that the creation of the monetary unit has induced positive trade/FDI effects for its member states.

[9] In specifying the latter variables, we follow Egger (2001) and Serlenga and Shin (2007).

We use roughly the same set of time-varying variables for the gravity models of FDI (both inward and outward), and as Brenton et al. (1999) point out, the economic interpretation of the explanatory variables is very similar: As in the case of trade, FDI is expected to be positively related to the level of income at home and abroad as a proxy for a large domestic market, and negatively to population indicating that large population sized countries are expected to be more self-sufficient in terms of investment. An alternative interpretation would be that a positive correlation of FDI with a country's population indicates an FDI engagement of vertical type, since population is expected to the more abundant production factor with a lower price for labor. For transition countries (such as East Germany and CEECs) one could also consider a different interpretation of the population coefficient. Here the population level may capture the market potential effect of FDI much better than GDP related variables, reflecting the underlying hypothesis that the latter variables are still below their long-run trends alongside the catching-up process. Hence, population levels as a proxy for the market potential effect are assumed to be positively correlated with FDI activity. As for trade, we also include the variables *SIM* and *RLF* in the FDI equations as a potential indicator of the bilateral share of horizontal or vertical investment activities. Thereby, two similar countries (in terms of absolute GDP levels and/or factor endowments) are expected to engage more in horizontal than vertical FDI.

For the FDI models, we additionally augment the vector of time-varying variables by further endowment based variables derived from the NTT (see e.g. Borrmann et al. 2005). We include labor force specific skill variables and factor prices in the host country such as aggregate wage levels as well as FDI agglomeration forces proxied by the degree of FDI openness of the host country (e.g. defined as total inward FDI stock relative to GDP or alternatively the total per capita capital stock of the host country). We expect that agglomeration forces are typically positively related to the FDI activity. The effect of the wage level in the host country is a priori not clear. If vertical FDI activities are the dominant driving force, it should turn negative; for a dominance of horizontal FDI, a positive relationship between the wage level and FDI activity could also be true (indicating the need for a qualified workforce in foreign affiliate production and sales).

The set of time-invariant variables (both in the trade and FDI equations) includes geographic distance as proxy for transportation costs in the case of trade or fixed plant set-up and monitoring costs in the case of FDI. The role of distance has become one of the major research topics in trade theory, while typically a negative influence on both variables is assumed in the gravity model literature (see e.g. Markusen and Maskus 1999).[10] We further specify a dummy variable for differences in the export/FDI behavior of the East German states to capture historical and/or structural

[10]However, Egger and Pfaffermayr (2004) argue that although distance can be regarded as an obstacle to both trade and FDI, the two variables still may be seen as complements (rather than substitutes) with respect to this proxy for trade costs depending on the relative importance of plant set-up costs versus pure trade costs. Trade theory suggests that firms will tend to engage in FDI at the costs of trade as transport costs (proxied by distance) rise. More distant markets will tend to be served by overseas investments in firm affiliates rather than by exporting. Their

differences between the two German macro regions. Based on earlier research, we test the hypothesis whether the East German firms are still below their trade and investment potential.[11] We also test for neighboring (border) effects and measure the deviation of trade and FDI from German regions to CEECs compared to the core of the EU15 member states.[12]

Generally, neighboring effects are assumed to have a positive impact on trade and FDI due to historical, cultural and personal ties between the trading and investment partners. The expectations about the trade and FDI volume of German regions with the CEECs is not that clear a priori. For bilateral trade, several studies have revealed that German trade with the CEECs has increased rapidly after the transformation of these countries towards market economies in the early 1990s and that trade volumes now are already above their potential (relative to a normal trade level derived from the gravity model's determining factors) so that the dummy coefficient for trade is expected to be positive in particular for exports from Germany to the CEECs.[13] With respect to the FDI stock, it is questionable whether the short time span after the transformation to market economies is sufficient to build up a normal FDI stock (in the sense of the gravity model estimates), we thus expect a negative sign for the dummy variable coefficient with respect to outward FDI. The same logic applies for inward FDI. A summary of theoretically motivated coefficient signs for the gravity equations is given in Table 5.1.

5.3 Theory and Empirics of Trade-FDI Linkages

This section serves to give a short overview of recent theoretical and empirical contributions in analyzing trade-FDI linkages.[14] One basic observation is that the theoretical literature is rather inconclusive on that point since both type of interaction channels—either favoring a complementary or substitutive relations among the variables—can be found. The Heckscher–Ohlin (H–O) model with perfectly competitive product markets and no transportation costs as the standard workhorse model of traditional trade theory, for instance, explains trade between two countries mainly on differences in factor endowments. In the absence of factor mobility

hypothesis thus gives rise to a further proposal on how the estimate gravity models of trade and FDI properly, namely in an adequate simultaneous equations specification that explicitly accounts for the common determinants.

[11] See Alecke et al. (2003).

[12] The CEEC aggregate includes Hungary, Poland, the Czech Republic, Slovakia, Slovenia, Estonia, Latvia, Lithuania, Romania and Bulgaria.

[13] See e.g. Collins and Rodrik (1991), Wang and Winters (1991), Hamilton and Winters (1992), Baldwin (1994), Schumacher and Trübswetter (2000), Buch and Piazolo (2000), Jakab et al. (2001), Caetano et al. (2002) as well as Caetano and Galleg (2003).

[14] Markusen (1995), Jungmittag (1995), Zarotiadis and Mylonidis (2005) and Blanchard et al. (2008) among others provide detailed surveys of recent theoretical contributions.

Table 5.1 Theoretically expected variable coefficients in the trade and FDI gravity equations

Variable	Code	Trade eqs.	FDI eqs.	Expected coef. sign
Gross domestic product in i/j	*GDP* (or $\frac{GDP}{POP}$)	X	X	(+) Trade/FDI activity increases with absolute higher income or welfare levels respectively (induced by higher supply and demand for differentiated varieties)
Population in i/j	*POP*	X	X	(+/−) with − = Self-sufficiency in production (resource endowments); alternatively Trade: + = Δ share of labor intensive trade; FDI: + = market potential theory of FDI
Similarity index of ij	*SIM*	X	X	(+/−) Trade: + = Δ share of intraindustry trade; FDI: + = Δ share of horizontal FDI
Relative factor endowments of ij	*RLF*	X	X	(+/−) Trade: + = Δ share of interindustry trade; FDI + = Δ share of vertical FDI
Labor productivity in i/j	*PROD*	X	X	(+) New Trade Theory: More productive firms on average higher degree of internationalization (expected to be higher for FDI than Trade)
Euro area dummy	*EMU*	X	X	(+) Trade/FDI creating effect of single currency
Wage level in j	*WAGE*		X	(−) Indicator for vertical cost oriented FDI engagement (only in outward FDI equation)
FDI openness in j	*FDIopen*		X	(+) Proxy for agglomeration forces at work (only in outward FDI equation)
Capital stock in j	*K*		X	(+/−) with + = Agglomeration forces or − = Neoclassical view (H–O) of higher expected return for relatively scare production factor (only in outward FDI equation)
Capital intensity in i	*KI*		X	(+/−) with + = Agglomeration forces or − = Neoclassical view (H–O) of higher expected return for relatively scare production factor (only in inward FDI equation)
Geographical distance of ij	*Dist*	X	X	(+/−) Trade: − = Transportation costs as obstacles to trade; FDI: + = FDI as alternative to trade for increasing distances, alternatively: − = Increasing monitoring costs over longer distance, increasing cultural differences etc.
East German State dummy	*East*	X	X	(+/−) A-priori unknown (possibly: − = Negative historical path dependency in East German internationalization process)
CEE Country dummy	*Ceec*	X	X	(+/−) A-priori unknown (possibly: − = Negative historical path dependency in CEEC internationalization process)
Common Border dummy	*Border*	X	X	(+) Positive neighboring effect on trade/FDI due to historical, cultural and personal ties

(FDI), international trade serves to equalize factor prices across countries. However, if factor mobility increases, the differences in endowments diminish and trade volumes tend to decrease. Surveying recent theoretical contributions, Markusen (1995) shows that the substitutive H–O model predictions can also be extended to the case of imperfect competition. A prominent approach of the latter type is the so-called proximity-concentration trade-off explored by Brainard (1993, 1997). Here, under the assumption of non-zero trade costs, the extent to which firms decide to engage in trade rather than foreign sales (FDI) depends crucially on the relative benefits of being close to the targeted market versus concentrating production in one location, which is associated with the exploitation of economies of scale.

On the contrary, recent contributions also derive complementaries between trade and FDI. A starting point is the General Equilibrium model of Helpman (1984), which models MNEs as vertically integrated firms in a monopolistic competition environment with their choice of location for (intermediate) production being driven by relative factor costs and resource endowments. In this set-up, FDI is more likely to create (inter-industry) trade rather than replace it. Consequently, from a vertically integrated modelling perspective, trade and FDI are complementary with respect to differences in factor endowments. Starting from a critical reflection of the proximity-concentration trade-off literature, Baldwin and Ottaviano (2001) show that complementary and substitutive elements in trade-FDI activity may coexist. In their model, multi-product final-good producing firms simultaneously engage in intra-industry trade and FDI based on the idea that obstacles to trade generate a natural incentive for multi-product firms to do so. In the model, non-zero trade costs shift production location to foreign affiliates so that, as a result, FDI displaces some exports (as standard trade theory result). However, it may also enhance trade via reverse imports of final goods since products in the model are differentiated. One of the advantages of the model is that the parallelism between the pattern of trade and investment is at the core of the model's driving mechanism. For our empirical analysis of German trade/FDI activity within the EU27, the model may be seen as especially relevant, since it is explicitly designed to explain the behavior of European MNEs and track the specific European trade-FDI pattern/nexus—with Europe being modelled as a rather closed trading area.

There are also various approaches aiming to pin down the trade-FDI-nexus empirically. Though on average there is a general tendency to reveal complementary linkages, the empirical literature also gives heterogeneous answers to this question. As Aizenman and Noy (2006) point out, important aspects to account for in the empirical set-up are to closely interpret the estimation result in light of the chosen country, industry sample and time period under observation. That is, for example, with respect to positive trade-FDI linkages much more empirical support is found in the context of developing rather than developed countries (see e.g. Tadesse and Ryan 2004). Another sensitive aspect is the sample period. As Pain and Wakelin (1998) point out, the nature of the trade-FDI linkage may change over time e.g. depending on the maturity of the investments and the accumulation of investments over time in terms of a country's stage of internationalization activity.

Empirical approaches may be broadly classified into macro and micro (firm-level) studies. The latter are typically characterized by a detailed sectoral disaggregation and accounts for firm heterogeneity, whereas the former analysis puts trade and FDI flows in its macroeconomic context. Aggregate data are predominantly estimated in a gravity model framework, mainly focusing on the link between exports and outward FDI. Selected results of the empirical literature for industrialized countries are as follows: For US data, Lipsey and Weiss (1981, 1984) find a positive coefficient in regressing US outward FDI stocks on exports. Subsequently Brainard (1997), Graham (1999), Clausing (2000), Egger and Pfaffermayr (2004) as well as Fontagne and Pajot (1997) support this complementary view. For the UK Zarotiadis and Mylonidis (2005) find positive ties between trade and FDI based on inward FDI stocks as well as both export and import data. In the case of Japan the picture is rather different with the majority of studies revealing substitutive linkages: A negative export-outward FDI nexus is e.g. reported in Ma et al. (2000) and Bayoumi and Lipworth (1997). Only Nakamura and Oyama (1998) find trade expansion effects of outward FDI. For other country pairs (including a macro-sectoral disaggregation) studies such as Bloningen (2001) for USA–Japanese trade and FDI relations as well as Goldberg and Klein (1999) for the USA and South American countries reveal mixed evidence with both complementary and substitutive elements depending on the chosen country and sector under considerations. Among the few studies using (West) German data, Jungmittag (1995) and Egger and Pfaffermayr (2004) identify substitutive relationships—however solely focusing on exports and outward FDI stock. We also add imports and inward FDI to the analysis.

5.4 Data and Stylized Facts

We use a panel data set for 16 German states (*Bundesländer*) and the EU27 member countries, which gives a total of 368 country pairs (16 states $\times$ 23 countries).[15] Our database covers a time period of 13 years (1993–2005). Due to data limitations, we have to cope with an unbalanced panel. Import and export data is balanced for the whole sample. In the FDI equation we distinguish between zero FDI stock and not reported values. The latter are handled as missing data while we substitute zero trade flows by a small constant while using log-linear gravity models. For an overview of different methods of dealing with zero trade flows in the gravity model context see e.g. Linders and de Groot (2006). Though Coe and Tamirisa (2002) show that the results may differ significantly when excluding zero flows in the log-linear specification, our results remain rather stable when using different proxies for these zeros. A complete list of variables and data sources is given in Table 5.2.

Before we turn to the specification of the empirical model, we highlight some stylized facts of German trade and FDI patterns both from an aggregated as well as

[15] We exclude Malta and Cyprus due to their specific characteristics as island economies. Further, we treat Belgium and Luxembourg as one single economy mainly due to the limited accessibility of statistical data.

Table 5.2 Data description and source

Variable	Description	Source
EX_{ijt}	Export volume, nominal values, in Mio. €	Destatis (2008)
IM_{ijt}	Import volume, nominal values, in Mio. €	Destatis (2008)
$FDIout_{ijt}$	Outward FDI stock, nominal values, in Mio. €	Deutsche Bundesbank (2008)
$FDIin_{ijt}$	Inward FDI stock, nominal values, in Mio. €	Deutsche Bundesbank (2008)
GDP_{it}	Gross domestic product, nominal values, in Mio. €	VGR der Länder (VGRdL 2008)
GDP_{jt}	Gross domestic product, nominal values, in Mio. €	Eurostat (2008)
POP_{it}	Population, in 1000	VGRdL (2008)
POP_{jt}	Population, in 1000	Groningen Growth & Development center (GGDC 2008)
SIM_{ijt}	$SIM = \log\left(1 - \left(\frac{GDP_{it}}{GDP_{it}+GDP_{jt}}\right)^2 - \left(\frac{GDP_{jt}}{GDP_{it}+GDP_{jt}}\right)^2\right)$	see above
RLF_{ijt}	$RLF = \log\left\vert\left(\frac{GDP_{it}}{POP_{it}}\right) - \left(\frac{GDP_{jt}}{POP_{jt}}\right)\right\vert$	see above
EMP_{it}	Employment, in 1000	VGRdL (2008)
EMP_{jt}	Employment, in 1000	EU Commission (2008)
$PROD_{it}$	$Prod_{it} = \left(\frac{GDP_{it}}{EMP_{it}}\right)$	see above
$PROD_{jt}$	$Prod_{jt} = \left(\frac{GDP_{jt}}{EMP_{jt}}\right)$	see above
K_{it}	Capital stock, nominal, in Mio. €	VGRdL (2008)
K_{jt}	Capital stock derived from GFCF via perpetual inventory method, nominal, in Mio. €	GFCF data from Eurostat (2008)
KI_{it}	$KI_{it} = \left(\frac{K_{it}}{POP_{it}}\right)$	see above
$FDIopen_{jt}$	$FDIopen_{jt} = \left(\frac{Total\ inward\ FDI_{jt}}{GDP_{jt}}\right)$	FDI: (2008), GDP: see above
$WAGE_{it}$	Wage compensation per employee, nominal, in 1000	VGRdL (2008)
$WAGE_{jt}$	Wage compensation per employee, nominal, in 1000	EU Commission (2008)
$DIST_{ij}$	Distance between state capital for Germany and national capital for the EU27 countries, in km	Calculation based on coordinates, calculation tool obtained from www.koordinaten.de
EMU	(0, 1)-dummy variable for EMU members since 1999	
$EAST$	(0, 1)-dummy variable for the East German states	
$CEEC$	(0, 1)-dummy variable for the Central and Eastern European countries	
$BORDER$	(0, 1)-dummy variable for country pairs with a common border	
t_{1993}–t_{2005}	Time effects for the years 1993–2005	

a regional perspective. One of the main characteristics of the German economy is its relative strong openness to international trade and FDI. In 2005 German exports accounted for approximately 9.5% of total worldwide merchandise flows—making Germany the world's leading exporting nation worldwide ahead of the USA (8.9%), China (7.5%) and Japan (5.9%). Taking a closer look at the bilateral trade pattern with Germany's major trading partners, for import flows six out of the ten major partners come from the EU27 and for exports these are even eight out of ten. The share of German-EU27 trade relative to worldwide trade is 67.2% (for the average of 1993–2005) and for imports it is almost equally high (64.8%). Compared to exports the EU27-wide outward FDI share is somewhat lower (51.9% between 1993–2005) but still amounts to a significant part.[16] The percentage share of the inward FDI stock from EU countries for this period is extremely high in the case of Germany (73.8% relative to total inward FDI).

Looking at German regional trade and FDI intensities (defined as regional trade/FDI per regional GDP), Table 5.3 reports regional differences relative to the German average (where the latter is normalized to one). States with the highest total export intensity are Bremen (1.83 for 2000–2005), Saarland (1.47) and Baden-Württemberg (1.36). The figures are roughly similar for total as well as intra-EU exports. One major exception is the Saarland which has a significantly higher intra-EU trade intensity (1.91) compared to the total trade intensity (1.47). Since Saarland has a common border with France (and strong historical and cultural ties), this may be seen as an indication of a positive trade effect of a common border and close distance ties to EU trading partners, which are typically tested in a gravity model context. The most import intensive regions apart from the city states Bremen and Hamburg are Hessen (1.12 for total imports between 2000 and 2005), North Rhine-Westphalia (1.12) and Saarland (1.45). Examining the differences between the two West and East German macro regions, Table 5.3 shows that the East German states trade roughly half as much as the German average indicating that the East German states are still less involved in international trade compared to their Western counterparts. Figure 5.1 displays the results graphically.

With respect to the FDI intensities Table 5.3 shows that the southern states Hessen (2.32 for the period 2000 to 2005), Baden-Württemberg (1.33) and Bavaria (1.15) have the highest outward FDI activity after adjusting for absolute GDP levels. For the five East German states (Brandenburg, Mecklenburg-Vorpommern, Saxony, Saxony-Anhalt and Thuringia), the outward FDI activity is extremely low (0.06 for total and 0.04 for intra-EU FDI stocks). Looking at inward FDI the West–East gap is somewhat smaller, mirroring the broad picture that the Eastern states throughout their economic transition process are able to act as a host country for FDI, but with little options for East German firms to actively invest abroad. The (macro) regional differences for German trade-FDI activity are also summarized graphically in Fig. 5.1. The regional perspective of German state export and FDI activity shows

[16] The remainder part of Germany's outward FDI stock is mainly directed to the US (29.6% in 2005).

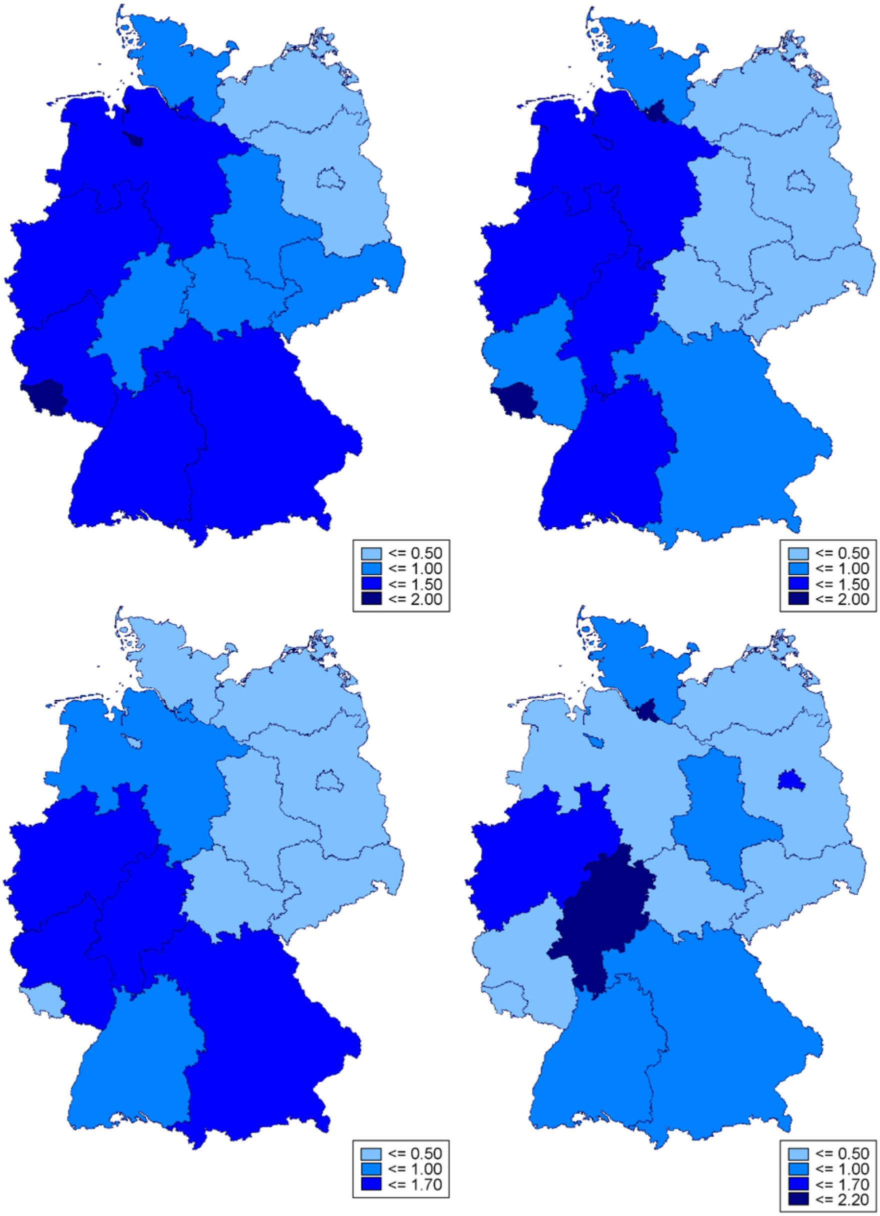

Fig. 5.1 Regional trade and FDI intensities within the EU27 for average 2000–2005 (with *upper left*: exports, *upper right*: imports, *lower left*: outward FDI, *lower right*: inward FDI). *Source*: See Table 5.3

that we detect strong regional difference for which we have to account when setting up a model that includes economic and geographic variables in explaining the German export and FDI performance.

Table 5.3 Relative export, import, outward and inward FDI intensity of German states compared to the national average (Germany = 1)

	Export intensity				Import intensity			
	Av. 1993–99		Av. 2000–05		Av. 1993–99		Av. 2000–05	
	World	EU27	World	EU27	World	EU27	World	EU27
BW	1.41	1.25	1.36	1.23	1.00	0.99	1.09	1.08
BAY	1.09	1.07	1.10	1.05	0.96	0.98	0.95	0.95
BER	0.46	0.42	0.46	0.42	0.31	0.35	0.33	0.33
BRA	0.31	0.35	0.42	0.44	0.46	0.44	0.54	0.42
BRE	1.97	1.70	1.83	1.64	2.62	1.45	1.87	1.36
HH	0.86	0.86	1.10	1.12	2.20	1.50	2.15	1.58
HES	0.82	0.82	0.71	0.69	1.27	1.19	1.12	1.08
MV	0.27	0.22	0.34	0.33	0.24	0.34	0.28	0.33
NIE	1.06	1.13	1.09	1.18	0.91	0.95	1.06	1.05
NRW	1.10	1.17	1.03	1.10	1.18	1.26	1.12	1.21
RHP	1.26	1.31	1.18	1.22	0.93	1.04	0.81	0.97
SAAR	1.43	1.76	1.47	1.91	1.25	1.64	1.45	1.97
SACH	0.36	0.41	0.68	0.61	0.33	0.44	0.43	0.48
ST	0.32	0.34	0.45	0.53	0.29	0.33	0.44	0.37
SH	0.69	0.66	0.73	0.74	0.75	0.82	0.82	0.90
TH	0.37	0.39	0.54	0.58	0.33	0.41	0.43	0.45
Germany	*1.00*	*1.00*	*1.00*	*1.00*	*1.00*	*1.00*	*1.00*	*1.00*
*East**	*0.33*	*0.36*	*0.52*	*0.52*	*0.34*	*0.40*	*0.43*	*0.43*
*West**	*1.11*	*1.11*	*1.09*	*1.09*	*1.12*	*1.11*	*1.11*	*1.11*

	Outward FDI intensity				Inward FDI intensity			
	Av. 1993–99		Av. 2000–05		Av. 1993–99		Av. 2000–05	
	World	EU27	World	EU27	World	EU27	World	EU27
BW	1.24	0.97	1.33	0.89	0.90	0.87	0.77	0.70
BAY	1.29	1.41	1.15	1.44	0.67	0.68	0.90	0.96
BER	0.50	0.62	0.24	0.28	0.73	0.82	1.04	1.14
BRA	0.06	0.06	0.02	0.03	0.32	0.46	0.27	0.31
BRE	0.27	0.41	0.10	0.15	1.03	1.24	0.76	0.81
HH	1.08	1.33	0.67	0.80	2.00	2.02	1.89	2.15
HES	2.02	2.03	2.32	1.65	2.59	1.95	2.34	1.88
MV	0.12	0.03	0.03	0.04	0.39	0.37	0.37	0.29
NIE	0.77	0.84	0.62	0.76	0.59	0.61	0.50	0.45
NRW	0.99	1.00	1.16	1.34	1.21	1.29	1.29	1.44
RHP	1.25	1.21	1.04	1.32	0.56	0.73	0.50	0.50

(*continued on the next page*)

Table 5.3 (Continued)

	Outward FDI intensity				Inward FDI intensity			
	Av. 1993–99		Av. 2000–05		Av. 1993–99		Av. 2000–05	
	World	EU27	World	EU27	World	EU27	World	EU27
SAAR	0.44	0.66	0.25	0.36	0.58	1.00	0.40	0.47
SACH	0.02	0.01	0.06	0.02	0.20	0.17	0.17	0.10
ST	0.11	0.00	0.01	0.00	0.97	1.70	0.59	0.78
SH	0.19	0.18	0.14	0.17	0.52	0.49	0.64	0.63
TH	0.06	0.06	0.06	0.15	0.23	0.35	0.23	0.15
Germany	*1.00*	*1.00*	*1.00*	*1.00*	*1.00*	*1.00*	*1.00*	*1.00*
*East**	*0.06*	*0.03*	*0.04*	*0.04*	*0.40*	*0.56*	*0.30*	*0.30*
*West**	*1.15*	*1.15*	*1.16*	*1.16*	*1.09*	*1.07*	*1.09*	*1.09*

Note: BW = Baden-Württemberg, BAY = Bavaria, BER = Berlin, BRA = Brandenburg, BRE = Bremen, HH = Hamburg, HES = Hessen, MV = Mecklenburg-Vorpommern, NIE = Lower Saxony, NRW = North Rhine-Westphalia, RHP = Rhineland-Palatine, SAAR = Saarland, SACH = Saxony, ST = Saxony-Anhalt, SH = Schleswig-Holstein, TH = Thuringia

Source: Data from Destatis (2008), Deutsche Bundesbank (2008), VGRdL (2008)

*East = East German states (excluding Berlin), West = West German states (excluding Berlin)

5.5 Econometric Specification and Estimation Results

5.5.1 Time Series Properties of the Variables

With the gravity model literature having its root in cross-sectional studies little attention has been typically paid to the time-series properties of the variables even if the empirical application now predominantly has switched to panel data estimation (exceptions are e.g. Fidrmuc 2009; Zwinkels and Beugelsdijk 2010). While for the standard microeconometric panel data model with $N \to \infty$ and fixed T, the assumption of stationarity may be seen as justified, it becomes less evident for macro panels with an increasing time dimension. Since our data with $N = 353$ and maximum $T = 13$ is at the borderline between classical micro and macro panel data, we aim to explicitly account for the time-series properties in order to avoid the problem of spurious regression among non-stationary variables that are not cointegrated.

Different approaches have been proposed to test for unit roots in panel data. However, only few are directly applicable to unbalanced data without inducing a bias to the test results (see e.g. Baltagi 2008, for an overview). Here we rely on a Fisher-type testing approach which averages the p-values of unit root tests for each cross section i as proposed by Maddala and Wu (1999) and Choi (2001). The null hypothesis of the test is that the series under observation is non-stationary. Fidrmuc (2009) alternatively proposes the CADF test from Pesaran (2007), which also works with unbalanced panel data. We use the CADF test to double check for those variables we do not reject the null hypothesis of a unit root in the series based on the Fisher-type test.

The results of the panel unit root tests for the variables in levels are given in Table 5.4. The results predominantly reject the null hypothesis of non-stationarity for

Table 5.4 Fisher-type and Pesaran (2007) panel unit root tests for variables in levels

Variables	χ^2-statistic of Fisher-type test (p-val.) H_0: Series non-stationary	
	Constant without trend	Constant and time trend
EX_{ijt}	813.08*** (0.00)	842.63*** (0.00)
$FDIout_{ijt}$	853.27*** (0.00)	687.85*** (0.00)
IM_{ijt}	1099.67*** (0.00)	821.67*** (0.00)
$FDIin_{ijt}$	602.89 (0.26)	579.81 (0.51)
GDP_{it}	1412.13*** (0.00)	1364.72*** (0.00)
GDP_{jt}	522.63 (0.96)	772.73*** (0.00)
POP_{it}	2744.13*** (0.96)	502.02 (0.99)
POP_{jt}	2171.32*** (0.00)	1160.79*** (0.00)
$PROD_{it}$	1224.90*** (0.00)	1669.38*** (0.00)
$PROD_{jt}$	413.19 (0.99)	827.45*** (0.00)
SIM_{ijt}	783.17*** (0.00)	1096.57*** (0.00)
RLF_{ijt}	565.87 (0.67)	1012.69*** (0.00)
$WAGE_{jt}$	554.41 (0.78)	759.67*** (0.00)
$FDIopen_{jt}$	628.54* (0.08)	233.97 (0.99)
K_{jt}	2387.88*** (0.00)	804.83*** (0.00)
KI_{it}	1609.78*** (0.00)	1084.10*** (0.00)
Critical Vars.	$\overline{CADF}$ for Pesaran (2007) test (p-val.) H_0: Series non-stationary	
	Constant without trend	Constant and time trend
$FDIin_{ijt}$	22.11	21.62
GDP_{jt}	−3.75***	4.94
POP_{it}	−3.67***	3.85
$PROD_{jt}$	−4.36***	5.58
RLF_{ijt}	−9.68***	−5.77***
$WAGE_{jt}$	−16.14***	−3.44***
$FDIopen_{jt}$	−6.38***	−0.29

Note: p-values are given in parenthesis. Critical values for the CADF test are taken from Pesaran (2003). These are for panel regression with $T = 15$, $N = 200$ including a regression constant but no trend: 1% (−2.16), 5% (−2.04), 10% (−1.98). For the test alternative with constant and time trend: 1% (−2.71), 5% (−2.57), 10% (−2.50)

*Denote statistical significance at the 10% level **Denote statistical significance at the 5% level

***Denote statistical significance at the 1% level

the variables in the dataset. However, both the Fisher-type unit root test as well as Pasaran's CADF test detect some cases which indicate non-stationarity of the time series. Since there is some heterogeneity with respect to the chosen test statistic, we are cautious in using the results unambiguously in favor of stationarity and additionally perform a residual-based unit root test for panel cointegration in the spirit of Kao (1999) on our final model specification to avoid the risk of running spurious regressions.

5.5.2 Econometric Specification

In estimating the system in (5.4)–(5.7) we carefully account for the trade-off between the likely increase in estimation efficiency based on a full information system approach (if we observe a significant correlation of the residuals from a single equation estimation of the respective gravity models) and the additional complexity brought into the system, which in turn may translate into increasingly biased results if the estimation error of one equation is transmitted to all other equations. The use of simultaneous equations models with panel data is not that common. However, Cornwell et al. (1992), Baltagi (2008), Baltagi and Chang (2000), Prucha (1984), Krishnakumar (1988) as well as Park (2005), among others, discuss both fixed effects and random effects panel data estimators in a system manner where right hand side endogeneity matters. The goal is to apply both IV and non-IV approaches to our simultaneous equation approach for the trade/FDI system. IV estimation thereby builds on the Hausman–Taylor (1981) model as the standard estimator in the field, while the non-IV alternative centers around a two-step estimator based on the Fixed Effects model, which has shown a good performance both in Monte Carlo simulations and empirical applications to gravity type models recently.

The Hausman–Taylor (1981) model may be seen as a hybrid version of the Fixed Effects (FEM) and Random Effects (REM) model. The idea of the Hausman–Taylor (HT) estimator is to derive consistent instruments from internal data transformations to cope with endogeneity, but still to avoid the strong all-or-nothing assumptions of the FEM and REM in terms of residual correlation of the right hand side regressors respectively. The Hausman–Taylor model therefore splits both the vectors of time-varying and time-fixed variables into two sub-vectors classifying the variables as either being correlated or uncorrelated with the unobservable individual effects. This classification scheme is then used to derive consistent instruments for model estimation.

We use the HT setup for estimating a 3SLS-GMM estimator, which has the advantage over standard 3SLS estimation because it allows the use of different instruments in subsequent equations of the system, while standard 3SLS assumes the same IV-set applies to every equation in the system. The latter assumption may be somewhat problematic in our case, since we have found that different instruments are valid for subsequent model equations based on a series of Hansen (1982)/Sargan (1958) overidentification tests for single equation benchmark models.[17] For convenience and in line with the mainstream literature on the Hausman–Taylor model, we assume that the variance-covariance (VCV) matrix of the error terms takes the random effects form.

[17]Results are not reported here, but can obtained upon request.

As alternative to the Hausman–Taylor IV estimator, we further apply a non-IV two-step modelling approach, which basically builds on the Fixed Effects Model (FEM) but also allows us to quantify the effect of time-fixed variables, which are wiped out by the within-type data transformation in the standard FEM. To avoid this problem, the two-step approach estimates the coefficient vector of the time-varying variables by FEM in a first step and then applies pooled OLS (POLS) in a second step to obtain a vector of coefficients for these variables that involves a regression of the first step group mean residuals (as a proxy for the unobserved individual effects) against the vector of time-fixed variables. Since this second step includes a generated regressand we have to adjust the standard errors. Due to the decomposition of the vector of fixed effects Plümper and Tröger (2007) label the estimator as Fixed Effects Vector Decomposition (FEVD).[18]

One advantage of the non-IV specification compared to the Hausman–Taylor approach is that no arbitrary ex-ante selection of consistent moment conditions (IVs) is necessary, and the approach avoids the risk of running into the weak-instrument problem, which may well apply to the former approach and result in a substantial finite sample bias. The FEVD-type two-step estimator has recently been applied in a variety of empirical contributions; especially for gravity type models (see e.g. Belke and Spies 2008, as well as Caporale et al. 2008). Small sample based Monte Carlo simulation experiments have confirmed the overall good empirical performance of this non-IV approach, which is found to be superior relative to the HT estimator especially in terms of getting the time-fixed variable coefficients right (see e.g. Plümper and Tröger 2007; Mitze 2009).

In the context of the FEVD-type two-step estimator the adaptation to a system approach is rather straightforward. That is, for the FEM model, Cornwell et al. (1992) show that in the absence of any assumption about the individual effects, one cannot do better than apply any efficient system estimator to the within-type transformed model. Analogously, for POLS—which ignores individual heterogeneity—the model can be directly applied in a seemingly unrelated regression (SUR) framework adjusting for the system's residual VCV matrix of the system by GLS estimation. In line with the FEVD single equation approach by Plümper and Tröger (2007), we will label the newly proposed system extension throughout the remainder of our analysis as FEVD-SUR. To adjust standard errors (SE) in the second step, we choose bootstrapping techniques as discussed in Atkinson and Cornwell (2006). We apply the wild bootstrap procedure, which has shown a good empirical performance in a variety of Monte Carlo simulation experiments (see e.g. Davidson and Flachaire 2001; MacKinnon 2002, and Atkinson and Cornwell 2006).[19]

For both the IV and non-IV approach, we apply the same estimation strategy. We first estimate the individual equations of the system in (5.4)–(5.7) and test for the cross-equation correlation of residuals, which indicate the use of a full information

[18]The reader is referred to Appendix A for a detailed discussion of the estimation settings of the FEVD.

[19]Additional details on the specification of both estimators including the bootstrapping procedure for the FEVD-SUR are given in Appendix A.

approach. On the fly, this approach allows us to derive a measure of the underlying trade-FDI linkages for our sample of German regions based on the first step estimates of the system's residual VCV matrix as pointed out by Egger and Pfaffermayr (2004). In this logic, elements beside the main diagonal in the VCV matrix of the (composed) error term can be used as estimates for the underlying state-country pair trade and FDI linkages. A negative parameter indicates a substitutive relationship between the two analyzed variables after controlling for common and observed exogenous determinants. The test setup may be seen as a straightforward extension to the standard approach to test for trade-FDI linkages, which typically employ simple pairwise residual correlations in an auxiliary regression (e.g. Graham 1999; Brenton et al. 1999; Pantulu and Poon 2003; Africano and Magalhaes 2005, among others). We use Breusch–Pagan (1980) type LM tests corrected for unbalanced panel data sets according to Song and Jung (2001) and Baltagi and Song (2006) to check for the significance of the cross-equation residual correlation.[20]

5.5.3 Estimation Results

Table 5.5 plots the results for the Hausman–Taylor 3SLS-GMM estimator and Table 5.6 reports the FEVD-SUR findings. The R^2 shows that both estimates are quite

Table 5.5 3SLS-GMM estimation results for Hausman–Taylor model

Dep. variable	HT-3SLS-GMM			
	Exports	FDI out	Imports	FDI in
$Log(GDP_i)$	0.94	5.11***	1.23**	2.58***
	(0.650)	(1.777)	(0.503)	(0.996)
$Log(GDP_j)$	0.12	0.93***	2.65***	5.56***
	(0.948)	(0.242)	(0.855)	(1.085)
$Log(POP_i)$	−1.55**	−3.35**	−0.42	1.35*
	(0.769)	(1.688)	(0.533)	(0.781)
$Log(POP_j)$	0.58***	2.31***	−1.88**	−6.49***
	(0.146)	(0.404)	(0.858)	(1.177)
$Log(PROD_i)$	2.01***	−3.92**		
	(0.638)	(1.904)		
$Log(PROD_j)$			−2.52***	−5.50***
			(0.821)	(1.092)
$Log(DIST_{ij})$	−1.23***	−3.21***	−1.53***	−2.88***
	(0.366)	(0.497)	(0.311)	(0.904)
$Log(WAGE_j)$		0.13		
		(0.271)		

(*continued on the next page*)

[20]Further details on the specification of the test statistic are given in Appendix B.

Table 5.5 (Continued)

Dep. variable	HT-3SLS-GMM			
	Exports	FDI out	Imports	FDI in
$Log(FDIopen_j)$		0.49^{***}		
		(0.131)		
$Log(KF_j)$		-0.95^{***}		
		(0.344)		
$Log(\frac{KBL_i}{POP_i})$				-2.26^{***}
				(0.678)
SIM	-0.37^{***}	1.24^{***}	-0.69^{***}	-0.52^{*}
	(0.102)	(0.349)	(0.248)	(0.317)
RLF	0.01	0.01	0.07^{**}	-0.06
	(0.010)	(0.034)	(0.034)	(0.041)
EMU	0.20^{***}	-0.51^{***}	0.04	0.57^{***}
	(0.041)	(0.143)	(0.067)	(0.164)
EAST	-0.79^{***}	-2.98^{***}	0.36	2.12^{***}
	(0.203)	(0.475)	(0.282)	(0.522)
BORDER	0.73	-1.22^{*}	0.29	-1.72
	(0.590)	(0.691)	(0.430)	(1.399)
CEEC	-0.48^{*}	-3.15^{***}	0.15	-3.99^{***}
	(0.285)	(0.533)	(0.359)	(0.629)
Time effects	Yes	Yes	Yes	Yes
(p-value of Wald test)	(0.00)	(0.00)	(0.00)	(0.00)
No. of system observation		10660		
No. of obs. per equation	2665	2665	2665	2665
No. of groups per equation	353	353	353	353
KP weak ident. F-test	38.64	85.12	147.98	21.98
Staiger–Stock rule ($F \geq 10$)	passed	passed	passed	passed
Hansen/Sargan overid.	8.67 (3)	9.98 (4)	8.53 (5)	42.86 (3)
(p-value)	(0.04)	(0.04)	(0.12)	(0.00)
$\|m\|$-stat. 3SLS/2SLS	0.01	28.56	42.26	36.54
(p-value)	(0.99)	(0.43)	(0.01)	(0.08)
Resid. based ADF test	766.4^{***}	1113.5^{***}	1579.9^{***}	1327.0^{***}
(p-value)	(0.00)	(0.00)	(0.00)	(0.00)
R^2	0.69	0.66	0.42	0.59

Note: Standard errors are robust to heteroscedasticity and clustering on bilateral pairs. Variable classification: $X1 = [GDP^1_{jt}, POP^1_{jt}, PROD^1_{jt}, POP^2_{jt}, POP^2_{it}, PROD^2_{jt}, WAGE^2_{jt}, KF^2_{jt}, GDP^3_{it}, GDP^3_{jt}, POP^3_{jt}, POP^3_{it}, PROD^3_{jt}, RLF^3_{ijt}, POP^4_{jt}, PROD^4_{jt}, KBLC^4_{it}, RLF^4_{ijt}]$ and $Z2 = [DIST^1_{ij}, DIST^2_{ij}, DIST^3_{ij}]$, where high level indices label the equation number as 1 = export, 2 = outward FDI, 3 = imports, 4 = inward FDI. Endogeneity of $Z2$ variables is tested based on the C-statistic
*Denote statistical significance at the 10% level **Denote statistical significance at the 5% level
***Denote statistical significance at the 1% level

Table 5.6 FEVD-SUR estimation results

Dep. variable	FEVD-SUR			
	Exports	FDI out	Imports	FDI in
$Log(GDP_i)$	0.62*	4.50***	1.56***	1.57***
	(0.356)	(1.263)	(0.215)	(0.572)
$Log(GDP_j)$	0.13**	−0.85	1.35***	4.91***
	(0.056)	(0.552)	(0.177)	(0.429)
$Log(POP_i)$	−1.57***	−1.30	−0.70	6.79***
	(0.527)	(1.847)	(0.455)	(1.314)
$Log(POP_j)$	2.17***	−0.52	2.89***	−0.70
	(0.410)	(1.440)	(0.548)	(1.345)
$Log(PROD_i)$	2.16***	−4.34***		
	(0.362)	(1.293)		
$Log(PROD_j)$			−1.12***	−5.22***
			(0.191)	(0.467)
$Log(DIST_{ij})$	−0.79***	−1.71***	−1.16***	−2.99***
	(0.051)	(0.189)	(0.068)	(0.165)
$Log(WAGE_j)$		1.22***		
		(0.453)		
$Log(FDIopen_j)$		0.05		
		(0.105)		
$Log(KF_j)$		−0.83**		
		(0.422)		
$Log(\frac{KBL_i}{POP_i})$				1.61***
				(0.431)
SIM	−0.33***	1.79***	−0.28***	0.03
		(0.206)	(0.073)	(0.172)
RLF	0.01	0.02	0.04***	−0.06***
	(0.007)	(0.025)	(0.009)	(0.022)
EMU	0.16***	−0.75***	−0.07**	0.35***
	(0.024)	(0.101)	(0.035)	(0.083)
EAST	−1.16***	−3.75***	−0.22	2.41***
	(0.294)	(0.775)	(0.341)	(1.001)
BORDER	0.71	1.04	−1.10	0.90
	(0.411)	(0.968)	(0.629)	(1.406)
CEEC	0.58**	−5.53***	−1.14***	−6.34***
	(0.293)	(0.826)	(0.393)	(1.207)

(*continued on the next page*)

Table 5.6 (Continued)

Dep. variable	FEVD-SUR			
	Exports	FDI out	Imports	FDI in
Time effects	Yes	Yes	Yes	Yes
(p-value of Wald test)	(0.00)	(0.00)	(0.00)	(0.00)
No. of system observation		10660		
No. of obs. per equation	2665	2665	2665	2665
No. of groups per equation	353	353	353	353
$\|m\|$-stat. SUR/OLS	9.60	10.39	63.93	8.92
(p-value)	(0.97)	(0.98)	(0.00)	(0.98)
$\|m\|$-stat. HT-SYS/FEVD-SYS	115.15	117.98	20.14	15.36
(p-value)	(0.00)	(0.00)	(0.44)	(0.80)
Resid. based ADF test	659.7**	1418.5***	1185.8***	1027.4***
(p-value)	(0.01)	(0.00)	(0.00)	(0.00)
R^2	0.53	0.58	0.63	0.58

Note: Standard errors are robust to heteroscedasticity, for a description of the wild bootstrap algorithm to adjust 2. step standard errors see text. The number of bootstrap repetitions is set to 1000
*Denote statistical significance at the 10% level **Denote statistical significance at the 5% level
***Denote statistical significance at the 1% level

close and explain a significant part of the total variation in the respective trade and FDI equations (around 50–70%). Taking a closer look at the individual equations' variable coefficients, we find that most key variables are estimated in line with our a-priori expectations. Output effects (both GDP for the home and foreign country) proxying the role of economic mass in bilateral trade and FDI activity play a distinct role. This is in line with our theoretical assumptions. Only for the export equation the results show a surprisingly low explanatory power of the income variables: Here the effect is mainly captured through labor productivity (defined as GDP per total employment). Econometrically, this latter result may hint at the strong link between labor productivity and export activity, which is broadly confirmed in the closely related micro-based literature (see e.g. Helpman et al. 2003; Arnold and Hussinger 2006).

All equations assign a crucial role to distance as a proxy for transportation costs in both trade/FDI, while the effect is found to be on average higher in the FDI rather than trade case. The latter result may reflect the likely path dependency in building up FDI stocks, since the rather more distant peripherical EU27 member states (from the geographical perspective of Germany) have only recently joined the EU (and thus adopted the institutional setup of the *aquis communitaire*). Moreover, the empirical result that distance exerts a stronger negative impact on foreign affiliate production than exports can be related to similar results in the recent literature (see e.g. Ekholm 1998).[21]

[21] Also Markusen and Maskus (1999) and Carr et al. (2001) among others report a significant negative influence of distance on outward FDI/foreign affiliate production.

For export activity the EMU dummy shows the a-priori expected positive impact on German exports for both estimators. From 1999 onwards, German export activity to the other EMU member states is estimated to be above its normal potential (in terms of being adjusted for economic mass, geographical distance and other explanatory variables as specified in the gravity model of (5.4)). For inward FDI, we find similar investment enhancing effects of EMU creation. The results are found to be robust for both the HT and FEVD estimator. However, on the contrary, the effect on outward FDI is found to be negative, possibly reflecting the general trend of stagnating or even decreasing German FDI stocks in the EMU countries contrary to non-EMU economies within the EU27 (especially a shift from the peripherical, southern Mediterranean EMU member states to the CEECs throughout the late 1990s). For imports, the estimated EMU coefficient turns out to be insignificant in the HT-case and only marginally negative in the FEVD-SUR approach. Also, with respect to the border dummy, we do not find any statistically significant result for both estimators.

The dummy variables for the East German states and CEEC economies turn out to be strongly negative in most specifications. For the export and outward FDI equation the East German states dummy is found to be significantly negative indicating that the macro region is still far beyond its trading potential, we would expect according to its economic mass and geographical location within the EU27.[22] On the contrary, for inward FDI equation, both estimators find a significant and positive coefficient for this dummy variable. This result mirrors the qualitative findings from the stylized facts, saying that the East German states throughout their economic transition process are limited to act as an FDI host country with little options to actively invest abroad. Moreover, the positive coefficient for the East German macro region in the inward FDI equation may reflect the large-scale investment promotion scheme for the East German economy jointly launched by the EU, federal and state level government, which significantly lowered the regional user costs of capital and led to an inflow of (foreign and West German) capital.

The results for the CEEC dummy in the export equation are somewhat mixed. While the HT model produces a (weakly significant) negative CEEC dummy, the FEVD output reports a positive coefficient sign. With respect to German exports to the CEECs, the latter positive dummy variable coefficient indicates that trade flows to these countries are above their normal potential, which has been widely confirmed in earlier empirical contributions for the first half of the 1990s.[23] On the contrary,

[22]Related to our results Alecke et al. (2003) find a significant negative dummy variable for East German states in a gravity model context for estimating German regional trade flows to Poland and Czech Republic.

[23]It remains an open question though whether this result is also expected to hold for the rapid economic catching up process of the CEECs. Moreover it is not clear whether Germany is likely to hold its first-mover advantages compared to the other EU15 countries: While Kunze and Schumacher (2003) predict a further boost in the German CEEC trade, Buch and Piazolo (2000) and Caetano et al. (2002) among others make projections based on gravity models that Germany throughout the 1990s has already exploited most of its trade potential with CEE countries, and that in the following other EU15 member states are expected to benefit most from the recent EU enlargement.

the CEEC dummy in the outward FDI equation is found to be significantly negative for both estimators indicating that German outward FDI stocks in these economies are still below their 'normal' potential. Moreover, the persistently negative CEEC dummy in the import and inward FDI equation reflect our a-priori expectations that these countries due to historical and structural reasons still have very limited capacities to export and invest abroad.

5.5.4 Robustness Checks

To check for the appropriateness of our empirical specification in the HT case, we compute a weak identification test to measure the degree of instrument correlation with the endogenous regressors to identify low correlation levels, which in turn may translate into a poor overall performance (see e.g. Stock and Yogo 2005). For the HT-3SLS-GMM model, all equations pass the weak identification test in terms of the Staiger and Stock (1997) rule of thumb ($F \geq 10$). We also apply the Sargan (1958)/Hansen (1982) test for overidentification of moment conditions. The results of the overidentification test show that, except for the inward FDI model, all chosen IV sets have rather low test statistics.[24] For the inward FDI equations all attempts to further reduce the number of moment conditions above those reported in Table 5.5 result in an instability of most variable coefficients so that we rely on the reported IV set even though it fails to pass the Sargan overidentification test.

To compare the appropriateness of our chosen full information system approach relative to a limited information benchmark, we employ the Hausman (1978) test (m-stat.). Under the assumption that the 3SLS estimator is generally more efficient than the 2SLS estimator, we test whether the difference between the two estimators is large, indicating that the more complex GLS transformation in the 3SLS case is likely to induce a misspecification in the model rendering it inconsistent. Thus, under the null hypothesis, both estimators are consistent, but only 3SLS is efficient. Under the alternative hypothesis only 2SLS is consistent.[25] For the FEVD model we use an analogous test framework comparing the SUR approach with the OLS benchmark. The results of the Hausman test in Tables 5.5 and 5.6 show that the full information techniques (both in the HT and FEVD case) pass the test for convenient confidence intervals in all equations except for imports. In sum we take these results in favor for our specified full information techniques.

In the spirit of Baltagi et al. (2003), we also employ a second Hausman test to check for the consistency and efficiency of the HT estimator against the FEVD

[24] Since the overidentification test tends to be very restrictive in terms of hypothesis rejection, we take tests results for which the null hypothesis of instrument appropriateness is not rejected at the 1% level in favor for the respective IV set in focus.

[25] By construction, if the 2SLS variance is larger than the 3SLS variance, the test statistic will be negative. Though the original test is typically not defined for negative values, here we follow Schreiber (2007) and take the absolute value of the Hausman m-stat. as indicator for rejecting the null hypothesis of 3SLS efficiency.

benchmark, where the latter builds upon consistent FEM estimation for the vector of time-varying variables. We thus have a testable null hypothesis for this parameter vector, while we cannot evaluate the consistency and efficiency of the vector of time-fixed variables. The results of this second Hausman test are reported in Table 5.6 and indicate that the difference between the two estimators is rather small for the import and inward FDI equation, where the null hypothesis of consistency and efficiency of the HT model cannot be rejected for convenient confidence intervals. However, for the export and outward FDI equation the null hypothesis is clearly rejected. Taken together with the empirical findings in Mitze (2009) that Hausman–Taylor type models tend to have a severe bias in estimating the coefficient vector of time-fixed variables, we favor the FEVD-SUR approach for our empirical application since it less sensitive to likely problems in IV selection. Finally, as indicated by the residual based ADF-test for cointegration in the spirit of Kao (1999), for both models we can reject the null hypothesis for non-stationarity in the residuals.

5.6 Identification of Trade-FDI Linkages

We find significant cross-equation correlations for both estimators. Given the favoring postestimation results from above we favor the FEVD-SUR estimates, which are nevertheless qualitatively broadly in line with the Hausman–Taylor results.[26] In Table 5.7 we plot the corresponding (rank) correlation coefficients for our four-equation residual based VCV matrix together with the Breusch–Pagan LM test results for unbalanced data. Additionally, we also compute a Harvey–Phillips (1982) type exact independence F-test, which checks for the joint significance of the other equations' residuals in an augmented first step regression (see e.g. Dufour and Khalaf 2002, for details).

We get significant evidence for both substitutive and complementary linkages among the variables under observation. Focusing on each type of international activity separately, for both the exports and imports as well as outward and inward FDI activity respectively we observe complementary (enhancing) effects. Turning to the trade-FDI linkages we find a substitutive relationship between exports and outward FDI activity in line with earlier evidence reported in Jungmittag (1995) as well as Egger and Pfaffermayr (2004). Also, imports and outward FDI are found to be of substitutive nature. However, on the contrary imports and inward FDI are found to complement each other, while the relationship between exports and inward FDI is tested insignificantly on the basis of Breusch–Pagan LM tests. As a sensitivity analysis we also estimate trade-FDI linkages for sub-aggregates of our data set as:

- West Germany—EU27/EU15,
- East Germany—EU27/EU15.[27]

[26] Results for the latter estimator can be obtained upon request from the authors.

[27] A further disaggregation is not feasible due to data limitations.

Table 5.7 Cross-equation residual correlation and Breusch–Pagan test for German—EU27

	Exports	FDI out	Imports	FDI in
Exports	1.00			
FDI out	-0.44^{***}	1.00		
	$\chi^2(1) = 71.9$			
Imports	0.53^{***}	-0.15^{***}	1.00	
	$\chi^2(1) = 95.5$	$\chi^2(1) = 8.69$		
FDI in	0.02	0.25^{***}	0.41^{***}	1.00
	$\chi^2(1) = 0.12$	$\chi^2(1) = 27.3$	$\chi^2(1) = 62.1$	
Harvey–Phillips (p-val.)	(0.00)	(0.00)	(0.00)	(0.00)

*Denote statistical significance at the 10% level **Denote statistical significance at the 5% level
***Denote statistical significance at the 1% level

Table 5.8 Cross-equation residual correlation and Breusch–Pagan test for West German—EU27

	Exports	FDI out	Imports	FDI in
Exports	1.00			
FDI out	-0.16^{**}	1.00		
	$\chi^2(1) = 4.01$			
Imports	0.33^{***}	0.19^{***}	1.00	
	$\chi^2(1) = 43.8$	$\chi^2(1) = 24.2$		
FDI in	0.14^{***}	0.35^{***}	0.71^{***}	1.00
	$\chi^2(1) = 9.69$	$\chi^2(1) = 53.7$	$\chi^2(1) = 140.9$	
Harvey–Phillips (p-val.)	(0.00)	(0.00)	(0.00)	(0.00)

*Denote statistical significance at the 10% level **Denote statistical significance at the 5% level
***Denote statistical significance at the 1% level

Our motivation for using these additional subsamples is that the data period from 1993–2005 covers the transformation period of the central and eastern European countries (including also the East German economy) from planned to market economies. Given the historical situation of these countries, we only observe a gradual opening up for internationalization activities with the core EU-15 member states over the sample period, which may well impact on the empirical results. We thus expect that trade-FDI ties are supposed to be strongest for the West German states with their respective EU-15 bilateral country pairs.

In Table 5.8, we see that the identified cross-equation correlations closely follow predictions of New Trade theory models such as Baldwin and Ottaviano (2001). That is, when international trade is merely of intra-industry type with non-zero trade costs, the latter shifts production abroad and leads to export replacement effects of FDI. However, at the same time FDI may stimulate trade via reverse good imports.

Table 5.9 Cross-equation residual correlation and Breusch–Pagan test for West German—EU15

	Exports	FDI out	Imports	FDI in
Exports	1.00			
FDI out	0.30***	1.00		
	$\chi^2(1) = 49.7$			
Imports	0.66***	0.13***	1.00	
	$\chi^2(1) = 124.5$	$\chi^2(1) = 9.67$		
FDI in	0.10***	0.75***	−0.03	1.00
	$\chi^2(1) = 7.80$	$\chi^2(1) = 150.7$	$\chi^2(1) = 0.33$	
Harvey–Phillips (p-val.)	(0.00)	(0.00)	(0.00)	(0.00)

*Denote statistical significance at the 10% level **Denote statistical significance at the 5% level
***Denote statistical significance at the 1% level

We thus find that export and outward FDI activity are still substitutes. However, all remaining trade-FDI links show complementary effects. In the model of Baldwin and Ottaviano (2001), this result is mainly driven by cross-hauling of FDI generating reciprocal trade effects in differentiated final products. Given the dominance of intra industry trade and horizontal FDI between West Germany and the EU27 economies as well as non-zero trade costs (as tested in our gravity model), these theoretical predictions may be seen as a good explanation for our empirically identified trade-FDI nexus in the case of West Germany. Moreover, a further disaggregation to West German—EU15 trade and FDI activity in Table 5.9 even reveals complementaries among export and FDI activity, which have not been identified for German data before, but generally match the mainstream empirical evidence in an international perspective. The latter result may be explained by the greater similarities in levels of development of West Germany and the EU15 compared to the enlarged EU including the new eastern member states, which is likely to have an effect on the horizontal/vertical nature of FDI. For the results for the East German macro region in Tables 5.10 and 5.11, we find merely substitutive linkages (except for inward FDI and trade in the East German—EU15 case), which may hint at the rather low level of internationalization activities (in particular outward FDI) of the East German macro region. Moreover, as for the West also for East Germany selective structural differences between the EU15 and the EU27 samples can be observed (e.g. with respect to inward FDI and trade variables), which may indicate the specific relation of East Germany with respect to the new Eastern EU member states.

To sum up, in addition to recent findings supporting the need of a sectoral disaggregation in analyzing trade-FDI linkages (e.g. Pfaffermayr 1996; Bloningen 2001; Türkcan 2007), our results show that the regional perspective within a nation's trade and FDI activity may also be of great importance in identifying cross-variable linkages. That is, while we find that the relationship between exports and inward FDI is found to insignificant at the aggregate level, regionally we find opposing effects

Table 5.10 Cross-equation residual correlation and Breusch–Pagan test for East German—EU27

	Exports	FDI out	Imports	FDI in
Exports	1.00			
FDI out	-0.48^{***}	1.00		
	$\chi^2(1) = 67.6$			
Imports	0.80^{***}	-0.44^{***}	1.00	
	$\chi^2(1) = 161.2$	$\chi^2(1) = 58.4$		
FDI in	-0.56^{***}	0.35^{***}	-0.55^{***}	1.00
	$\chi^2(1) = 113.8$	$\chi^2(1) = 44.1$	$\chi^2(1) = 113.7$	
Harvey–Phillips (p-val.)	(0.00)	(0.00)	(0.00)	(0.00)

*Denote statistical significance at the 10% level **Denote statistical significance at the 5% level
***Denote statistical significance at the 1% level

Table 5.11 Cross-equation residual correlation and Breusch–Pagan test for East German—EU15

	Exports	FDI out	Imports	FDI in
Exports	1.00			
FDI out	-0.44^{***}	1.00		
	$\chi^2(1) = 75.5$			
Imports	0.77^{***}	-0.45^{***}	1.00	
	$\chi^2(1) = 168.9$	$\chi^2(1) = 74.6$		
FDI in	0.76^{***}	-0.40^{***}	0.69^{***}	1.00
	$\chi^2(1) = 161.6$	$\chi^2(1) = 62.3$	$\chi^2(1) = 152.9$	
Harvey–Phillips (p-val.)	(0.00)	(0.00)	(0.00)	(0.00)

*Denote statistical significance at the 10% level **Denote statistical significance at the 5% level
***Denote statistical significance at the 1% level

(a positive one between West Germany—EU27, a negative one for East Germany—EU27) which on average may cancel out a total net effect. A similar interpretation can be given to the strong negative correlation between exports and outward FDI in the case of East Germany, which is likely to influence the aggregate results. This latter result may especially stem from the fact that for our sample period, the dynamics of integration to world markets for East Germany is much higher due to its low starting levels and putting distinct choice option on the mode of internationalization.[28] The identified trade-FDI linkages are shown in Table 5.12.

[28]It is not clear whether this result can be captured in a level effect, or whether the assumption of slope homogeneity for the time varying variables is not valid for the underlying German regions (see e.g. Pesaran and Yamagata (2008)). Future research should put more effort on this question, especially when longer time dimensions of the variables are available.

Table 5.12 Identified trade-FDI linkages for different data samples

	Exports	FDI out	Imports	FDI in
Germany—EU27				
Exports	*			
FDI out	negative	*		
Imports	positive	negative	*	
FDI in	insign.	positive	positive	*
West Germany—EU27				
Exports	*			
FDI out	negative	*		
Imports	positive	positive	*	
FDI in	positive	positive	positive	*
West Germany—EU15				
Exports	*			
FDI out	positive	*		
Imports	positive	positive	*	
FDI in	positive	positive	insign.	*
East Germany—EU27				
Exports	*			
FDI out	negative	*		
Imports	positive	negative	*	
FDI in	negative	positive	negative	*
East Germany—EU15				
Exports	*			
FDI out	negative	*		
Imports	positive	negative	*	
FDI in	positive	negative	positive	*

5.7 Conclusion

The aim of this chapter was to analyze the main macroeconomic driving forces for German regional and national trade and FDI activity within the EU27 and to identify their correlations. We have used the gravity approach as a modelling framework and base our identification strategy on the inclusion of appropriate exogenous control variables as proposed in the gravity model literature. With respect to the underlying trade-FDI linkages at the aggregate level, we basically find a substitutive relationship between exports and outward FDI activity in line with earlier evidence reported in Jungmittag (1995) as well as Egger and Pfaffermayr (2004). Also, imports and outward FDI are found to be substitutive, while imports and inward FDI complement each other.

We also estimated trade-FDI links for regional sub-samples. That is, for West German—EU27 trade/FDI activity, we find strong support for the predictions of NTT models as in Baldwin and Ottaviano (2001). When international trade is of merely intra-industry type with non-zero trade costs, the latter shifts production abroad and leads to export replacement effects of FDI. However, at the same time FDI may stimulate trade via reverse good imports. Thus, export and outward FDI are found to be substitutes for each other, while all remaining variable linkages show complementary effects. The latter result may indicate the growing importance of vertical FDI in our sample period from 1993 to 2005, which may be especially driven by a boost of investment activity in the new EU member states. Moreover, a further disaggregation into West German—EU15 trade/FDI activity even reveals complementaries among export and FDI activity, which have not been identified for German data before, but match with the general empirical evidence in an international context. For the East German states, we overwhelmingly find substitutive linkages (except for inward FDI and trade in the East German—EU15 case), which may indicate the rather low level of internationalization activities (in particular outward FDI) of the East German macro region.

When interpreting these results, we have to account for our chosen country sample and time period. While our results make sense for intra-EU trade and FDI activity, a generalization to overall trade-FDI activity has to be done carefully.[29] These caveats have to be taken into account when the results are used in the policy debate for export and/or FDI promotion schemes. Our results also indicate to look at regional disaggregation when modelling trade and FDI patterns and identifying underlying cross-variable linkages. Future research effort should be done in explicitly testing for the significance of other factors driving internationalization activity besides those already captured in our approach (such as exchange rates) as well as to more carefully account for the likely caveats when operationalizing the gravity model. This latter point may comprise explicit tests for the poolability of the data (see e.g. Pesaran and Yamagata 2008) as well as the appropriate functional form.

Appendix A: IV and Non-IV System Estimators

A.1 The General Model

We start from a general, triple indexed model form as:

$$y_{ijt} = \alpha + \beta' X_{ijt} + \gamma' Z_{ij} + u_{ijt} \quad \text{with } u_{ijt} = \mu_{ij} + \nu_{ijt}, \tag{5.8}$$

with $i = 1, 2, \ldots, N$; $j = 1, 2, \ldots, M$ and $t = 1, 2, \ldots, T$. The endogenous variable (y_{ijt}) and the vector of time varying explanatory variables (X_{ijt}) may vary in all

[29] Even though German-EU27 trade and FDI pattern accounts for a large share of total trade and FDI activity. Moreover, using a world sample Cechella et al. (2008) recently found that world FDI is also mainly driven by horizontal motives.

three dimensions of our model, while the vector of time fixed explanatory variables (Z_{ij}) is kept constant across t. β and γ are vectors of regression coefficients, α is the overall constant term and u_{ijt} is the composed error term including the unobservable individual effects μ_{ij} and a remainder error term ν_{ijt}. Typically the latter two are assumed to be i.i.d. residuals with zero mean and constant variance. For system estimation we may write (5.8) compactly as:

$$y_n = R_n \xi_n + u_n, \quad u_n = \mu_n + \nu_n, \tag{5.9}$$

where n denotes the nth structural equation of the system with $n = 1, \ldots, M$. In our case $M = 4$. $R_n = (X_n, Z_n)$ and $\xi = (\beta', \gamma')$. Following Cornwell et al. (1992) we then simply stack the equations into the usual 'starred' form as:

$$y_* = R_* \xi_* + u_*, \tag{5.10}$$

where $y'_* = (y'_1, \ldots, y'_N)$ and similar for ξ_* and u_*. R_* is defined as

$$R_* = \begin{bmatrix} R_1 & \cdots & 0 \\ \vdots & \ddots & \vdots \\ 0 & \cdots & R_M \end{bmatrix}. \tag{5.11}$$

Depending on the type of estimator we can make use of the seemingly unrelated regression (SUR) approach or 3SLS estimation to the stacked system in (5.10). Thereby, the SUR model may be seen as a special case of the more general 3SLS estimator when there is no right hand side endogeneity in the estimated equations (for details see e.g. Intrilligator et al. 1996). The SUR approach is popular since it captures the correlation of the disturbances across equations and—if the disturbance terms are correlated—it is asymptotically more efficient than OLS for each single equation. However, for the case we have to cope with endogeneity of the right-hand side regressors of the model either in the sense of endogenous variables as explanatory variables in other equations of the system or a correlation of some regressors with the disturbances, Baltagi (2008) proposes to use 3SLS for estimating (5.10).

A.2 The HT-3SLS-GMM Estimator

Since the logic of the Hausman–Taylor model centers around consistent IV estimation of all parameters in the model, the 3SLS estimator is the natural choice (or in a broader context system GMM).[30] Next to consistent IV choice for estimation purposes one also has to decide about the proper empirical form of the system's error term variance-covariance matrix. In its standard form the model typically builds on the random effects assumption in line with Baltagi's (1981) feasible EC-3SLS es-

[30] The system extension to the standard single equation Hausman–Taylor models was first proposed by Cornwell et al. (1992), a GMM version of the estimator is discussed in Ahn and Schmidt (1999).

timators as probably the most prominent example in the field of system estimation with Panel data. As Cornwell et al. (1992) show, the EC-3SLS estimator can be interpreted as a special form of the more general HT-3SLS framework, namely when all exogenous variables are assumed to be independent of the system's error components. Alternatively, Ahn and Schmidt (1999) propose to start with an unrestricted covariance matrix in the context of optimal system GMM estimation and then test for valid model (variance-covariance) restrictions. For the purpose of this analysis we specify the Hausman–Taylor model in its 3SLS-GMM form as:

$$\hat{\beta}_{3SLS\text{-}GMM} = [R_*' H_* (H_*' \hat{\Omega} H_*)^{-1} H_*' R_*]^{-1} R_*' H_* (H_*' \hat{\Omega} H_*)^{-1} H_*' y_*, \tag{5.12}$$

where H_*^S is the system's total IV set based on the definition $H_i^S = I_M \otimes H_i$ (with H_i as the nth equation instrument set) and $u_i^S = (u_{1i}', \ldots, u_{M,i}')$, so that we can write the system's overall set of moment conditions compactly as $E(H_i^{S'} u_i^S) = 0$. The latter in turn is chosen according to th Hausman–Taylor assumptions. $\hat{\Omega} = \text{Cov}(u_*)$ is the variance-covariance matrix of the equation system. The main difference between the standard 3SLS estimator and its 3SLS-GMM alternative is that the latter allows for different instruments in subsequent equations, while standard 3SLS estimation assumes the same IV-set applies to every equation in the system. The latter assumption may be somewhat problematic in our case, since we have found that different instruments are valid for subsequent model equations based on a series of Hansen (1982)/Sargan (1958) overidentification tests for the single equation benchmark models.[31]

For convenience and in line with the mainstream literature on the Hausman–Taylor model we assume that Ω_* takes the random effect form.[32] We thus model the two error components μ and ν as i.i.d. with $(0, \Sigma_\mu)$ and $(0, \Sigma_\nu)$, where $\Sigma_\mu = [\sigma^2_{\mu(j,l)}]$ is the 4×4 variance-covariance matrix corresponding to the unobserved individual effects (with $j, l =$ [exports, FDI out, imports, FDI in]) and $\Sigma_\nu = [\sigma^2_{\nu(j,l)}]$ is the 4×4 variance-covariance matrix of the remainder error term. For unbalanced panel data the variance-covariance varies with ij and therefore transforming the estimation system by $\Omega_{ij}^{-1/2}$ takes the following form:

$$\Omega_{ij}^{-1/2} = (\Sigma_\nu + T_{ij} \Sigma_\mu)^{-1/2} \otimes P + \Sigma_\nu^{-1/2} \otimes Q. \tag{5.13}$$

In empirical terms we use the feasible GLS approximation in order to replace the unknown parameters of covariance matrix, Σ_ν and $(\Sigma_\nu + T_{ij} \Sigma_\mu)$ by consistent estimates. To derive these proxies we follow Baltagi's (2008) suggestion for unbalanced panels and estimate the respective sub blocks (or matrix elements) of $\hat{\Sigma}_\nu$ and $\hat{\Sigma}_\mu$ as

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[31] Results can be obtained upon request from the authors.

[32] An alternative choice for Ω_* would be an unrestricted form in analogy to the optimal weighting matrix for system GMM as $\Omega = (I_N \otimes \Sigma_{j,l})$, where $\Sigma_{j,l}$ can be estimated from any consistent 1.step residuals according to $\Sigma_{j,l} = N^{-1} \sum_{i=1,j=1}^{NM} (\hat{u}_j \hat{u}_l')$ (see Ahn and Schmidt 1999, for details).

$$\hat{\sigma}^2_{\nu_{(j,l)}} = \frac{\hat{u}'_{j,l} Q \hat{u}_{j,l}}{\sum_{i=1,j=1}^{NM} (T_{ij} - 1)}, \tag{5.14}$$

$$\hat{\sigma}^2_{\mu_{(j,l)}} = \frac{\hat{u}'_{j,l} P \hat{u}_{j,l} - NM \hat{\sigma}_{\nu_{(j,l)}}}{\sum_{i=1,j=1}^{NM} (T_{ij})}, \tag{5.15}$$

where $\hat{u}$ is the estimation residual from an untransformed 1. step 2SLS estimation (see also Baltagi 2008, or Baltagi and Chang 2000, for details).[33]

A.3 The FEVD(-SUR) Estimator and Bootstrapping Standard Errors

An alternative to the Hausman–Taylor IV-estimator is an augmented FEM approach proposed by Plümper and Tröger (2007) for the single equation case. The goal of the so-called Fixed Effects Vector Decomposition (FEVD) model is to run a consistent FEM model and still get estimates for the time-invariant variables. The intuition behind FEVD specification is as follows: The unobservable individual effects are a vector of the mean effect of omitted variables, including the effect of time-invariant variables. According to Plümper and Tröger (2007) it is therefore possible to regress the proxy for individual effects derived from the FEM residuals on the time-invariant variables to obtain approximate estimates for these variables. The estimator builds on the following steps: First, we apply a standard FEM on (5.8) to obtain the vector of time-varying variable β. Second, we use the estimated vector of group residuals as proxy for the unobservable individual effects $\hat{\mu}_{ij}$ to run a regression of the explanatory time-fixed variables against this 'generated regressand' as:

$$\hat{\mu}_{ij} = \omega + \hat{\delta}' Z_{ij} + \eta_{ij}, \tag{5.16}$$

where ω is an overall intercept and η_{ij} is the residual. The second step aims at identifying the unobserved parts of the individual effects. In a third (optional) step Plümper and Tröger re-estimate (5.8) in a POLS setup including the 2. step residual η_{ij} to control for collinearity between time-varying and time-fixed right hand side variables. Finally, it is important that standard errors for the time-fixed variable coefficients have to be corrected due to the use of a 'generated regressand' in the 2. modelling step to avoid an overestimation of t-values. To sum up, the FEVD 'decomposes' the estimated proxy for the unobservable individual effects obtained from the FEM residuals into one part explained by the time-fixed variables and a remainder error term. Plümper and Tröger argue that one major advantage of the FEVD compared to the Hausman–Taylor model is that there is no need for any arbitrary ex-ante variable classification for consistent IV selection.

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[33] Finally, in the system transformation process we follow Baltagi (2008) and apply the Cholesky decomposition to Σ_ν^{-1} and Σ_μ^{-1}.

However, as shown in Mitze (2009) although the researcher is not confronted with the choice of classifying variables as being exogenous or endogenous with respect to the error term, the FEVD itself makes an implicit choice: That is, in specifying the time-varying variables the model follows the generality of the FEM approach, which assumes a variable correlation of unknown form. With respect to the time invariant variables the estimator on the other hand assumes in its basic form that none of the time-fixed variable is correlated with the individual effects.[34] If the implicit (and fixed) choice of the FEVD does not reflect the true correlation between the variables and the error term the estimator may perform poor. However, Monte Carlo simulations by Alfaro (2006), Plümper and Tröger (2007) and Mitze (2009) show that even if the FEVD does not meet the underlying true orthogonality conditions of the data set, due to is robust non-IV specification it has a smaller bias and prediction errors than consistent Hausman–Taylor specification especially for estimating the coefficients of both endogenous and exogenous time-fixed variables.

As outlined in Sect. 5.4, the system extension to the FEVD is rather straightforward. To correct standard errors in the resulting FEVD-SUR approach we apply the 'wild bootstrap' technique, which is implemented through the following steps as outlined in Atkinson and Cornwell (2006):[35]

Step 1 Estimate the coefficient vector $\hat{\beta}_{FEM\text{-}SUR}$ of X_{it} in a SUR system based on the within-type transformed data (FEM).

Step 2 Using the coefficient vector $\hat{\beta}_{FEM\text{-}SUR}$, we compute

$$\hat{\pi}_i = \bar{y} - \hat{\beta}_{FEM\text{-}SUR}\bar{X}_i. \tag{5.17}$$

Step 3 Estimate the coefficient vector $\hat{\gamma}_{POLS\text{-}SUR}$ for Z_i by POLS-SUR.

Step 4 Compute the second step residuals as

$$\hat{\xi}_{it} = y_{it} - \hat{\beta}_{FEM\text{-}SUR}X_{it} - \hat{\gamma}_{POLS\text{-}SUR}(J_T \otimes Z_i). \tag{5.18}$$

According to the 'wild bootstrap' procedure replace $\hat{\xi}_{it}$ with

$$\tilde{\xi}_{it} = (\hat{\xi}_{it})\tilde{\upsilon}_{it} \quad \text{where } f(\hat{\xi}_{it}) = \frac{\hat{\xi}_{it}}{(1-h_{it})^{1/2}} \tag{5.19}$$

and h is the model's projection matrix so that a division by $(1-h_{it})^{1/2}$ ensures that the transformed residuals have the same variance (for details see MacKinnon 2002); $\tilde{\upsilon}_{it}$ is defined as a two-point distribution (the so-called Rademacher distribution) with

$$\tilde{\upsilon}_{it} = \begin{cases} -1 & \text{with probability } 1/2, \\ 1 & \text{with probability } 1/2. \end{cases} \tag{5.20}$$

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[34] In fact, a modification of the FEVD also allows for the possibility to estimate the second step as IV regression and thus account for endogeneity among time invariant variables and η_{ij}. However, this brings back the classification problem from the Hausman–Taylor specification, which we explicitly aim to avoid by non-IV estimation.

[35] For notational convenience the cross-section dimension is expressed by i rather than ij here.

Step 5 For each of $i = 1, \ldots, N$ blocks, we draw randomly with replacement T observations with probability $1/T$ from $\tilde{\upsilon}_{it}$ to obtain $\tilde{\xi}^*_{it}$.
Step 6 Generate

$$y^*_{it} = \hat{\beta}_{FEM\text{-}SUR} X_{it} - \hat{\gamma}_{POLS\text{-}SUR}(J_T \otimes Z_i) + \tilde{\xi}^*_{it}. \tag{5.21}$$

Step 7 Compute the FEM-SUR for the vector of variable coefficients β using the starred data as $\beta^*_{FEM\text{-}SUR}$.
Step 8 Using $\beta^*_{FEM\text{-}SUR}$ from the previous step to compute

$$\omega_i = \bar{\tilde{\xi}}_i - (\hat{\beta}^*_{FEM\text{-}SUR} - \hat{\beta}_{FEM\text{-}SUR})\bar{X}_i. \tag{5.22}$$

Step 9 Randomly resample with replacement from $\hat{u}_i$ to obtain u^*_i. Then compute

$$\pi^*_i = \hat{\gamma}_{POLS\text{-}SUR} Z_i + u^*_i. \tag{5.23}$$

Step 10 Estimate the coefficients $\gamma^*_{POLS\text{-}SUR}$ using the starred data.
Step 11 Repeat steps 5–9 1000 times and compute the sample standard deviation of $\gamma^*_{POLS\text{-}SUR}$ as an estimator of the standard error of $\hat{\gamma}_{POLS\text{-}SUR}$.

Appendix B: Testing for Cross-Equation Residual Correlation

In order to analyze the statistical significance of the identified cross-equation residual correlation we use Breusch–Pagan (1980) type tests corrected for unbalanced panel data sets according to Song and Jung (2001) and Baltagi and Song (2006).[36] The Breusch–Pagan LM test on the correlation of individual effects across equations can be defined as

$$BP = \left(\frac{1}{2}\right) n^2 [A^2/(J - n)], \tag{5.24}$$

$$\text{with } J = \sum_{i=1, j=1}^{NM} T_{ij} \times (T_{ij} - 1),$$

$$A = [(u_j \Delta_1 \Delta'_1 u_l)/((u'_j u_j)(u'_l u_l))^{1/2}],$$

$$\Delta_1 = (D'_1, D'_2, \ldots, D'_T)',$$

where n is the number of total observations and D_t is obtained from an identity matrix I_{NM} by omitting the rows corresponding to individuals not observed in year t (with $j, l =$ [exports, FDI out, imports, FDI in]). As Baltagi (2008) shows, this can be easily done by restacking the residuals such that all the individuals observed in the first period are stacked on top of those observed in the second period, and so on. In this case, the slower index is t and the faster index is i, the error term (in vector form) can be written as $u = \Delta_1 \mu + \nu$. Testing for the cross-equation correlation

[36] Rather than using one-sided Honda (1985) type tests as proposed by Egger and Pfaffermayr (2004), since the cross equation covariance elements can actually become negative.

of the overall error term, $\Delta_1\Delta_1'$ chancels out (see e.g. Dufour and Khalaf 2002). Under the null hypothesis of no correlation, the Breusch–Pagan type LM test given by (5.24) is asymptotically distributed as $\chi^2(1)$.

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Chapter 6
Estimating Gravity Models of Trade with Correlated Time-Fixed Regressors: To IV or not IV?

6.1 Introduction

In contemporary panel data analyses, researchers are often confronted with the problem of parameter inconsistency due to the correlation of some of the explanatory variables with the model's error term. Assuming that this correlation is typically due to unobservable individual effects (see, e.g., Mundlak 1978), a consistent approach to deal with such type of right-hand-side endogeneity is to apply the standard fixed effects model (FEM), which uses a within-type data transformation to erase the unobserved individual effects from the model. However, one drawback of this estimator is that the within transformation also wipes out all explanatory variables that do not change in the time dimension of the model. In this case, no statistical inference can be made for these variables if they have been included in the original untransformed model based on theoretical grounds.

The researcher's problem is then to find an alternative estimator, which is still capable of including time-fixed regressors in the estimation setup. A well-known example for the above sketched estimation setup in empirical work is the gravity model (of trade, capital or migration flows among other interaction effects), which assigns a prominent role given to time-fixed variables in the regression model. Taking the gravity model of trade as an example, the model is a highly used for applied econometric work. With the recent switch from cross-section to panel data specifications, important shortcomings of earlier gravity model applications have been tackled (see e.g. Matyas 1997; Breuss and Egger 1999, as well as Egger 2000). However, other methodological aspects such as the proper functional form of the gravity equation are still subject to open debate in the recent literature (see, e.g., Baldwin and Taglioni 2006, and Henderson and Millimet 2008, for an overview). Recently, the time series properties of gravity models have also been more intensively studied (see, e.g., Fidrmuc 2008; Zwinkels and Beugelsdijk 2010).

In this chapter we focus on proper estimation strategies for gravity–type and related models when some time-varying and -fixed right-hand-side regressors are correlated with the unobservable individual effects. Baltagi et al. (2003) have shown that when endogeneity among the right-hand-side regressors matters, the OLS and

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random effects estimators are substantially biased and both yield misleading inference. As an alternative solution the Hausman–Taylor (1981, thereafter HT) approach is typically applied. The HT estimator allows for a proper handling of data settings when some of the regressors are correlated with the individual effects. The estimation strategy is basically based on instrumental variable (IV) methods, where instruments are derived from internal data transformations of the variables in the model. One of the advantages of the HT model is that it avoids the 'all-or-nothing' assumption with respect to the correlation between explanatory regressors and error components that is made in the standard FEM and REM approaches, respectively. However, for the HT model to be operable, the researcher needs to classify variables as being correlated and uncorrelated with the individual effects, which is often not a trivial task.

As a response to this drawback, in empirical application of the HT approach different estimation strategies have been suggested that strongly rely on statistical testing to reveal the underlying correlation of the variables with the model's residuals. Given the fact that the HT estimator employs variable information that lies in between the range of the FEM and REM, Baltagi et al. (2003), for instance, suggest using a pre-testing strategy that either converts to a FEM, REM or HT-type model depending on the underlying characteristics of the variable correlation in focus. The estimation strategy centers on the standard Hausman (1978) test, which has been evolved as a standard tool to judge among the use of the REM vs. FEM in panel data settings. Ahn and Low (1996) additionally propose a reformulation of the Hausman test based on the Sargan (1958)/Hansen (1982) statistic for overidentifying restrictions. Together with the closely related C-statistic derived by Eichenbaum et al. (1988), which allows testing single instrument validity rather than full IV sets, the Hansen–Sargan overidentification test may thus be seen as a more powerful tool to guide IV selection in the HT approach compared to the standard Hausman test.

As an alternative to IV estimation, different 'two-step'-type estimators have been proposed recently. Plümper and Tröger (2007), for instance, set up an augmented FEM model that also allows for the estimation of time-fixed parameters. Their model labeled fixed effects vector decomposition (FEVD) may be seen as a rival specification for the HT approach in estimating the full parameter space in the model including both time-varying and time-fixed regressors. The idea of the two-step estimator is to first run a consistent FEM model to obtain parameter estimates of the time-varying variables. Using the regression residuals as a proxy for the unobserved individual effects, in a second step this proxy is regressed against the set of time-fixed variables to obtain parameter values for the latter. Since this second step includes a 'generated regressand' (Pagan 1984), the degrees of freedom have to be adjusted to avoid an underestimation of standard errors (see, e.g., Atkinson and Cornwell 2006, for a comparison of different bootstrapping techniques to correct standard errors in these settings).[1] Though it is typically argued that one main advantage of these non-IV estimators is their freedom of any arbitrary classification

[1] In a recent comment, Greene (2010) criticizes the original approach by Plümper and Tröger (2007) arguing that they use a wrong variance covariance matrix resulting in systematically underestimated standard errors. Thus, bootstrapping the latter may be seen as a more appropriate choice.

of right-hand-side regressors as being endogenous or exogenous, as we will show later on, two-step estimators such as the FEVD also rests upon an implicit choice that may impact upon estimator consistency and efficiency.

Given the growing number of empirical applications of the latter non-IV FEVD approach (see e.g. Akther and Daly 2009; Belke and Spies 2008; Caporale et al. 2008; Etzo 2007, and Krogstrup and Wälti 2008; Mitze et al. 2010 among others), a systematic comparison of the HT instrumental variable approach with the non-IV FEVD is of great empirical interest regarding their small sample performance.[2] However, there are relatively few existing studies comparing the two-step estimators with the Hausman–Taylor IV approach in a Monte Carlo simulation experiment (in particular, Plümper and Tröger 2007, as well as Alfaro 2006). Moreover, in these studies as well as the broader Monte Carlo based evidence on the HT estimator (see, e.g., Ahn and Low 1996; Baltagi et al. 2003), the empirically unsatisfactory assumption is made that the true underlying correlation between right-hand-side variables and the error term is known. Our approach therefore explicitly offsets from earlier simulation studies and allows for the existence of imperfect knowledge in the HT model estimation with IV selection based on different model/moment selection criteria (see, e.g., Andrews 1999; Andrews and Lu 2001). The latter combines information from the Sargan/Hansen overidentification test and time-series information-criteria such as AIC and BIC. This allows for an empirical comparison of the HT and FEVD (two-step) estimators' performances, which comes much closer to the true estimation problem researchers face in applied modelling work in terms of "To IV or not IV?".

The remainder of the chapter is organized as follows: Sect. 6.2 briefly sketches the HT and non-IV FEVD alternative. In Sect. 6.3, we present the results of our Monte Carlo simulation experiment. Section 6.4 illustrates the empirical relevance by adding an empirical application to trade estimates in a gravity model context for German regions (NUTS1-level) within the EU27. Section 6.5 gives concluding remarks of the chapter.

6.2 Panel Data Models with Time-Fixed Regressors

We consider a general static (one-way) panel data model of the form

$$y_{it} = \beta X_{it} + \gamma Z_i + u_{it} \quad \text{with } u_{it} = \mu_i + \nu_{it}, \tag{6.1}$$

where $i = 1, 2, \ldots, N$ is the cross-section dimension and $t = 1, 2, \ldots, T$ the time dimension of the panel data. X_{it} is a vector of time-varying variables, Z_i is a vector of time invariant right-hand-side variables, β and γ are coefficient vectors. The error term u_{it} is composed of two error components, where μ_i is the unobservable individual effect and ν_{it} is the remainder error term. μ_i and ν_{it} are assumed to be $\mu_i \sim N(0, \sigma_\mu)$ and $\nu_{it} \sim N(0, \sigma_\nu)$ respectively.

[2] Searching for the term "Fixed Effects Vector Decomposition" (in quotation marks) by now gives almost 2100 entries in Google.

Standard estimators for the panel data model in (6.1), which control for the existence of individual effects are the FEM and REM approaches. However, choosing among the FEM and REM estimators rests on an 'all-or-nothing' decision with respect to the assumed correlation of right-hand-side variables with the error term. In empirical applications, the truth may often lie in between these two extremes. This idea motivates the specification of the Hausman–Taylor (1981) model as a hybrid version of the FEM/REM using IV techniques. The HT approach therefore simply splits the set of time-varying variables into two subsets $X_{i,t} = [X1_{i,t}, X2_{i,t}]$, where $X1$ are supposed to be exogenous with respect to μ_i and $\nu_{i,t}$. $X2$ variables are correlated with μ_i and thus endogenous with respect to the unobserved individual effects.[3] An analogous classification is done for the set of time-fixed variables $Z_i = [Z1_i, Z2_i]$. Note that the presence of $X2$ and $Z2$ is the cause of bias in the REM approach. The resulting HT model can be written as

$$y_{i,t} = \alpha + \beta_1' X1_{i,t} + \beta_2' X2_{i,t} + \gamma_1' Z1_i + \gamma_2' Z2_i + u_{i,t}. \tag{6.2}$$

The idea of the HT model is to find appropriate internal instruments to estimate all model parameters. Thereby, deviations from group means of $X1$ and $X2$ serve as instruments for the variables (in the logic of the FEM), $Z1$ serve as their own instruments and group means of $X1$ are used to instrument the time-fixed $Z2$. The FEM and the REM can be derived as special versions of the HT model, namely when all regressors are correlated with the individual effects the model reduces to the FEM. For the case that all variables are exogenous (in the sense of no correlation with the individual effects), the model takes the REM form. In empirical terms the HT model is typically estimated by GLS and throughout the analysis we use a generalized instrumental variable (GIV) approach proposed by White (1984), which applies 2SLS to the GLS-filtered model (including the instruments) as[4]

$$\tilde{y}_{i,t} = \tilde{\alpha} + \beta_1' \widetilde{X1}_{i,t} + \beta_2' \widetilde{X2}_{i,t} + \gamma_1' \widetilde{Z1}_i + \gamma_2' \widetilde{Z2}_i + \tilde{u}_{i,t}, \tag{6.3}$$

where $\tilde{y}_{i,t}$ denotes GLS-transformed variables (for details see, e.g., Baltagi 2008). Finally, the order condition for the HT estimator to exist is $k_1 \geq g_2$. That is, the total number of time-varying exogenous variables k_1 that serve as instruments has to be at least as large as the number of time invariant endogenous variables (g_2).[5] For the case that $k_1 > g_2$ the equation is said to be overidentified and the HT estimator obtained from a 2SLS regression is generally more efficient than the within estimator (see Baltagi 2008).

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[3]Here, we use the terminology of 'endogenous' and 'exogenous' to refer to variables that are either correlated with the unobserved individual effects μ_i or not. An alternative classification scheme used in the panel data literature classifies variables as either 'doubly exogenous' with respect to both error components μ_i and $\nu_{i,t}$ or 'singly exogenous' to only ν. We use these two definitions interchangeably here.

[4]One also has to note that the HT model can also be estimated based on a slightly different transformation, namely the filtered instrumental variable (FIV) estimator. The latter transforms the estimation equation by GLS but uses unfiltered instruments. However, both approaches typically yield similar parameter estimates, see Ahn and Schmidt (1999).

[5]The total number of IVs in the HT model is $2k_1 + k_2 + g_1$ ($k_1 + k_2$ from $QX1$ and $QX2$, k_1 from $PX1$ and g_1 from $Z1$).

In empirical applications of the HT approach, the main points of criticism focus on the arbitrary IV selection in terms of $X1/X2$ and $Z1/Z2$ variable classification as well as the poor small sample properties of IV methods when instruments are weak. Moreover, also the GLS transformation may be subject to a small sample bias. As an alternative estimation strategy given the shortcomings of the HT approach, recent two-step non-IV specifications such as the fixed effects vector decomposition (FEVD) by Plümper and Tröger (2007) have been proposed.[6] The goal of the model is to run a consistent FEM model and still get estimates for the time-invariant variables. The intuition behind the FEVD specification is as follows: Since the unobservable individual effects capture omitted variables including time-invariant variables, it should therefore be possible to regress a proxy of the individual effects obtained from a first stage FEM regression on the time-invariant variables to obtain estimates for these variables in a second step. Finally, the number of degrees of freedom for the use of a 'generated regressand' in this second step has to be corrected (e.g. by bootstrapping methods, see Atkinson and Cornwell 2006). We can thus sum up the FEVD estimator as

1. Run a standard FEM to get parameter estimates ($\hat{\beta}_{FEVD}$) of the time-varying variables.
2. Use the estimated group residuals as a proxy for the time-fixed individual effects $\hat{\pi}_i$ obtained from the first step as $\hat{\pi}_i = (\bar{y}_i - \hat{\beta}_{FEM}\bar{X}_i)$ to run an OLS regression of the explanatory time-invariant variables against this vector to obtain parameter estimates of the time-fixed variables ($\hat{\gamma}_{FEVD}$).

The residual term from the second step, $\hat{\eta}_i$, is composed of $\hat{\eta}_i = \zeta_i + \bar{X}_i(\hat{\beta}_{FEM} - \beta)$, where $\zeta_i = \mu_i + \bar{\nu}_i$ and the bar indicates the sample period mean for cross-section i as $\bar{X}_i = 1/T\sum_{t=1}^{T} X_{i,t}$.[7] One has to note that standard errors have to be corrected for $\hat{\gamma}_{FEVD}$ either asymptotically or by bootstrapping techniques (see Murphy and Topel 1985, as well as Atkinson and Cornwell 2006) to avoid an overestimation of t-values. To sum up, the FEVD 'decomposes' the vector of unobservable individual effects into a part explained by the time invariant variables and an error term. Since the FEVD is built on the FEM it yields unbiased and consistent estimates of the time-varying variables. According to Plümper and Tröger one major advantage of the FEVD compared to the HT model is that the estimator does not require prior knowledge of correlation between the explanatory variables and the individual effects.

However, estimates of the time-invariant variables are only consistent if either the time invariant variables fully account for the individual effects or the unexplained part of η_i is uncorrelated with the time-invariant variables. Otherwise, the FEVD also suffers from omitted variable bias.[8]

[6]The FEVD may be seen as an extension to an earlier model in Hsiao (2003). For details, see Plümper and Tröger (2007).

[7]For details see Atkinson and Cornwell (2006).

[8]A modification of the standard FEVD approach also allows for the possibility to estimate the second step as IV regression and thus account for endogeneity among time invariant variables and

Thus, though we are not directly confronted with the choice of classifying variables as endogenous or exogenous, the estimator itself does rely on an implicit choice. In specifying the time-varying variables, the model follows the generality of the FEM approach, which assumes that these variables are possibly correlated with the unobservable individual effects (for estimation purposes, deviations from group means are used which wipe out the individual effects so that no explicit assumption about the underlying correlation needs to be stated). With respect to the time-invariant variables, the estimator assumes in its simple form that no time-fixed variable (Z) is correlated with the second step error term, which is composed of the unobservable individual effects. However, if this implicit (and fixed) choice does not reflect the true correlation between the variables and the individual effects, the estimator may in fact only be an inconsistent alternative to the HT approach.

6.3 Monte Carlo Simulation Results

We run Monte Carlo simulations in the spirit of Im et al. (1999) and Baltagi et al. (2003) for the FEVD and HT estimator using different combinations of the cross-section (N) and time-series (T) dimension. Details about the simulation design are given in Appendix A. We use a static one-way model as in (6.1) including four time-varying (X) and three time-fixed (Z) regressors of the form

$$\begin{aligned} y_{i,t} &= \beta_{11} x_{1_1,i,t} + \beta_{12} x_{1_2,i,t} + \beta_{21} x_{2_1,i,t} + \beta_{22} x_{2_2,i,t} \\ &\quad + \gamma_{11} z_{1_1,i} + \gamma_{12} z_{1_2,i} + \gamma_{21} z_{2_1,i} + u_{i,t}, \quad \text{with } u_{i,t} = \mu_i + \nu_{i,t} \end{aligned} \tag{6.4}$$

where x_{1_1} and x_{1_2} are assumed to be uncorrelated with the error term, while x_{2_1} and x_{2_2} are correlated with μ_i. Analogously, z_{2_1} is correlated with the error term. The latter is composed of the unobserved individual effects (μ_i) and remainder disturbance ($\nu_{i,t}$). Since we are interested in consistency and efficiency of the respective estimators, we compute the empirical bias, its standard deviation and the root mean square error (rmse). The bias is defined as

$$bias(\hat{\delta}) = \sum_{m=1}^{M} (\hat{\delta} - \delta_{true})/M, \tag{6.5}$$

where $m = 1, 2, \ldots, M$ is the number of simulation runs, $\hat{\delta}$ is the estimated coefficient evaluated with respect to its true value. Next to the standard deviation of the

η_i. Following Atkinson and Cornwell 2006, we can define a standard IV estimator as: $\hat{\gamma}_{FEVD} = (S'Z)^{-1} S'\hat{\pi}$, where S is the instrument set that satisfies the orthogonality condition $E(S\,\eta) = 0$. However, this brings back the classification problem of the HT approach, which we aim to avoid here.

estimated bias we also calculate the rmse, which puts a special weight on outliers, as

$$rmse(\hat{\delta}) = \sqrt{\left(\sum_{m=1}^{M}(\hat{\delta} - \delta_{true})/M\right)^2}. \tag{6.6}$$

We first take a closer look at the individual parameter estimates for the parameter settings $N = 1000$, $T = 5$ and $\xi = 1$, which are typically assumed in the standard panel data literature building on the large N, small T data assumption.[9] In Fig. 6.1, we plot kernel density distributions for all regression coefficients for the following three estimators: (i) the FEVD, (ii) the HT model with perfect knowledge about the underlying variable correlation with the error term and (iii) the HT model based on the MSC-BIC algorithm (in its restricted form). The latter estimator is based on model selection criteria (MSC) that center around the J-statistic augmented by a 'bonus' term rewarding models with more moment conditions. Since the resulting MSC specifications are closely related to the standard information criteria AIC, BIC and HQIC, we label them MSC-AIC, MSC-BIC and MSC-HQIC respectively.

Additionally, we define a C-statistic-based model selection criteria. All criteria are applied to IV selection in the HT case. We apply both conservative IV selection rules, where instruments are not allowed to pass certain critical values of the J- and/or C-statistic in order to be selected, as well as less restrictive counterparts. Details are given in Appendix A. In the figure, we focus on the MSC-BIC based HT model since it shows on average the best performance among all HT estimators with imperfect knowledge about the underlying data correlation, closely followed by the C-statistic based model selection algorithm.

For the coefficients of the two exogenous time-varying variables β_{1_1} and β_{1_2}, all three estimators give unbiased results centering around the true parameter value of one. The standard deviation and rmse are the smallest for the HT model with perfect knowledge about the underlying data correlation, followed by the MSC-algorithm-based HT estimators. The FEVD has a slightly higher standard deviation and rmse. For the estimated coefficients of the endogenous time-varying variables β_{2_1} and β_{2_2} the HT and FEVD give virtually identical results, while the HT-based MSC-BIC in Fig. 6.1 is slightly biased for β_{2_1} but comes closer to the true parameter value for the parameter β_{2_2}. To sum up, though there are some minor differences among the three reported estimators for the time-varying variables in Fig. 6.1, the overall empirical discrepancy is rather marginal.

This picture however radically changes for the Monte Carlo simulation results of the time-fixed variable coefficients γ_{1_2} and γ_{2_1}. Here, only the HT model with the ex-ante correctly specified variable correlation gives unbiased results for both the exogenous (γ_{1_2}) and endogenous variable (γ_{2_1}). Both the FEVD and HT model based on the MSC-BIC have difficulties in calculating these variable coefficients

[9] ξ defines the ratio of the variance terms of the error components as $\xi = \sigma_\mu/\sigma_\nu$.

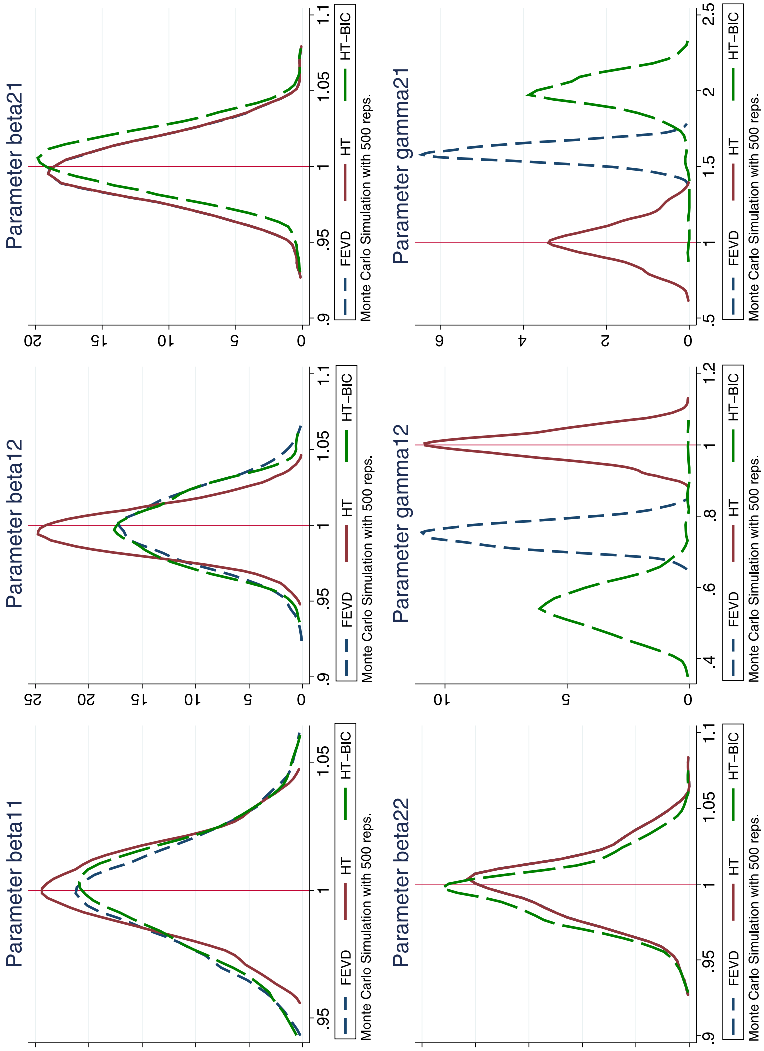

Fig. 6.1 Kernel density plots for Monte Carlo simulation results with $N = 1000$, $T = 5$, $\xi = 1$

correctly, while the bias of the FEVD is lower than for the MSC-BIC Hausman–Taylor model in both cases. Especially for γ_{2_1}, all HT-based model-selection algorithms exclusively have a large bias/standard deviation as well as a high rmse relative to the HT with perfect knowledge about the variable correlation with the error term. The FEVD has a significant bias (approximately 50 percent higher than the standard HT), but compared to the MSC-BIC-based specification, a lower bias/standard deviation.

Turning to the small sample properties, we reduce the number of cross-sections to $N = 100$ and leave the other parameters unchanged. For the time-fixed variables, the FEVD and the MSC-BIC-based HT model again have a significant bias, while the HT model with perfect knowledge about the underlying variable correlation comes, on average, much closer to the true parameter value (in particular for γ_{1_2}). However, as already observed in Plümper and Tröger (2007), the standard deviation of the latter estimator is much higher compared to the other two estimators. The results in Fig. 6.2 indicate that the HT instrumental variable approach is inefficient in small sample settings, though the average bias is small.

The specific problem of the MSC-BIC-based HT model in small sample settings becomes obvious in Fig. 6.1. Different from the standard HT and FEVD estimators, the MSC-BIC-based HT model shows a clear double peak for most parameters. For the coefficient of the endogenous time-fixed variable $\hat{\gamma}_{2_1}$, the estimates show one peak around the true coefficient value of one and a second significantly biased one. This kind of duality problem with a possibly poor MSC-based estimator performance has already been addressed in Andrews (1999) for those cases where there are typically two or more selection vectors that yield MSC values close to the minimum and parameter estimates that differ noticeably from each other. As the histogram in Fig. 6.3 shows, this is indeed the problem for the MSC-BIC-based HT model. For Monte Carlo simulation runs with 500 repetitions, the algorithm tends to pick two dominant IV-sets from which one has the (inconsistent) REM form with a full instrument list, while only the second one consistently excludes $Z21$ from the instrument list. These results may be seen as a first indication that, in small samples, J-statistic based IV selection has a low power and yields inconsistent results.

Turning from a comparison of single variable coefficients to an analysis of overall measures of bias and efficiency for an aggregated parameter space, we compute NOMAD and NORMSQD values, where the NOMAD (normalized mean absolute deviation) computes the absolute deviation of each parameter estimate from the true parameter, normalizing it by the true parameter and averaging it over all parameters and replications considered. The NORMSQD computes the mean square error (mse) for each parameter; normalizing it by the square of the true parameter, averaging it over all parameters and taking its square root (for details, see Baltagi and Chang 2000). Both overall measures are thus extensions to the single parameter bias and rmse statistics defined above. We compare the FEVD model with the standard HT model and the algorithm based HT models using the C-statistic approach, as well as the MSC-BIC, MSC-HQIC, MSC-AIC.

Summary results are reported in Table 6.1, disaggregated surface plots for the time-varying and time-fixed variable coefficients over all different settings are

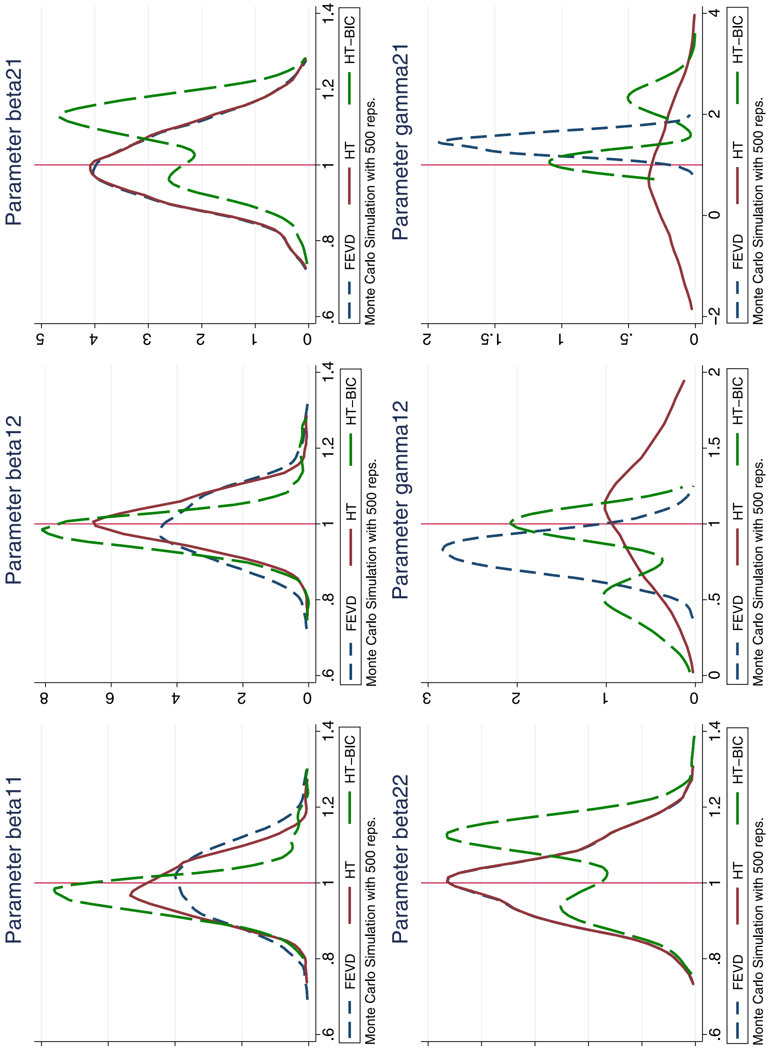

Fig. 6.2 Kernel density plots for Monte Carlo simulation results with $N = 100$, $T = 5$, $\xi = 1$

Fig. 6.3 Histogram of selected IV-sets for simulation results of γ_{21} with $N = 100$, $T = 5$, $\xi = 1$

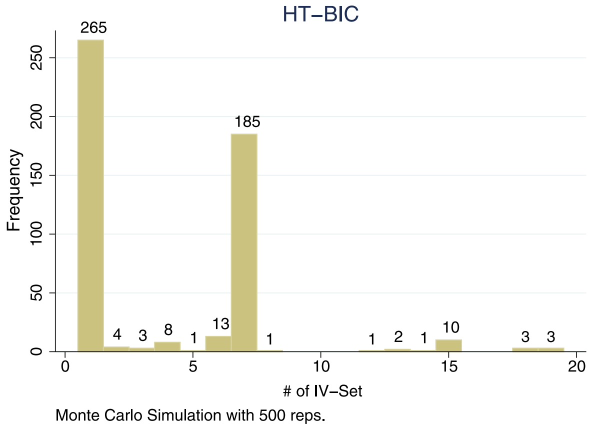

Table 6.1 NOMAD and NORMSQD averaged over all MC simulations

	Model	NOMAD	NORMSQD
Time-varying	FEVD	0.0009	0.0321
	HT	0.0029	0.0292
	HT-Cstat	0.0030	0.0321
	HT-BIC1	0.0086	0.0337
	HT-HQIC1	0.0099	0.0346
	HT-AIC1	0.0058	0.0329
Time-fixed	FEVD	0.4105	0.0672
	HT	0.1911	0.1888
	HT-Cstat	0.6009	0.2615
	HT-BIC1	0.6171	0.1990
	HT-HQIC1	0.6238	0.1952
	HT-AIC1	0.6231	0.2132
All variables	FEVD	0.2057	0.0497
	HT	0.0970	0.1090
	HT-Cstat	0.3019	0.1468
	HT-BIC1	0.3129	0.1164
	HT-HQIC1	0.3168	0.1149
	HT-AIC1	0.3144	0.1230

Note: For details about the Monte Carlo simulation setup and the definition of the HT estimators based on model selection criteria see Appendix A. The HT-BIC, HT-HQIC and HT-AIC algorithms are based on restricted MSC specifications in order to maximize the likelihood of consistent instrument selection

shown in Figs. 6.4–6.7. The table shows that the HT model with perfect knowledge about the underlying variable correlation has the lowest NOMAD value, with the FEVD having two times and algorithm based HT specification even three times higher values for the average bias over all model coefficients. For the latter the C-statistic based model selection criteria performs slightly better than the MSC based estimators. On the contrary, with respect to the NORMSQD, by far the best model is the non-IV FEVD. The difference between the standard HT model and

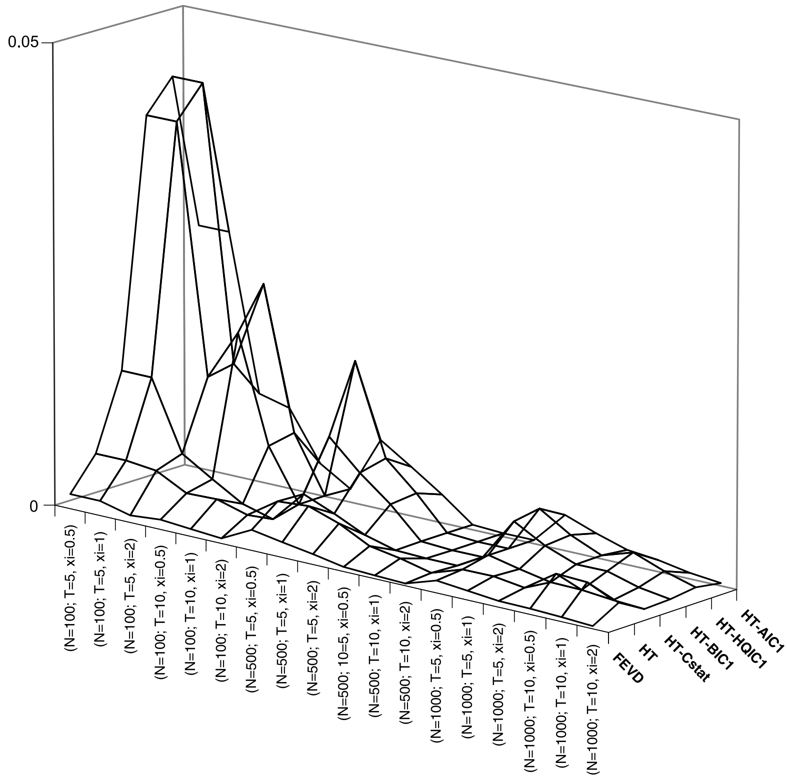

Fig. 6.4 NOMAD surface plot for time-varying variables in MC simulations

the algorithm-based specification is rather low. This broad picture indicates that the HT instrumental variable model is a consistent estimator given perfect knowledge about the true underlying correlation between the right hand side variables and the error term. However, when one has to rely on statistical criteria to guide moment condition selection the empirical performance for the specific setup in the Monte Carlo simulation design is considerably lower. This, in turn, speaks in favor of using non-IV two step estimators such as the FEVD, which has the lowest rmse due to its robust OLS estimation approach compared to the HT estimators.

We finally decompose the overall performance for time-varying and time-fixed coefficients. The choice of disaggregation is motivated by the above findings that the results significantly differ with respect to time-varying and time-fixed variable coefficients. Figures 6.4 and 6.5 plot NOMAD and NORMSQD values for the time-varying coefficients β_{1_1} to β_{2_2}. The figures show that the search-algorithm-based HT models show a significant small sample bias, while the NOMAD of the FEVD and standard HT is rather small for different combinations in the time and cross-section dimension of the data. In terms of the NORMSQD, all estimators show a similar pattern with improving performance for rising NT. Despite this general trend, Figs. 6.4 and 6.5 both show distinct spikes for low values for $\xi = 0.5$, which

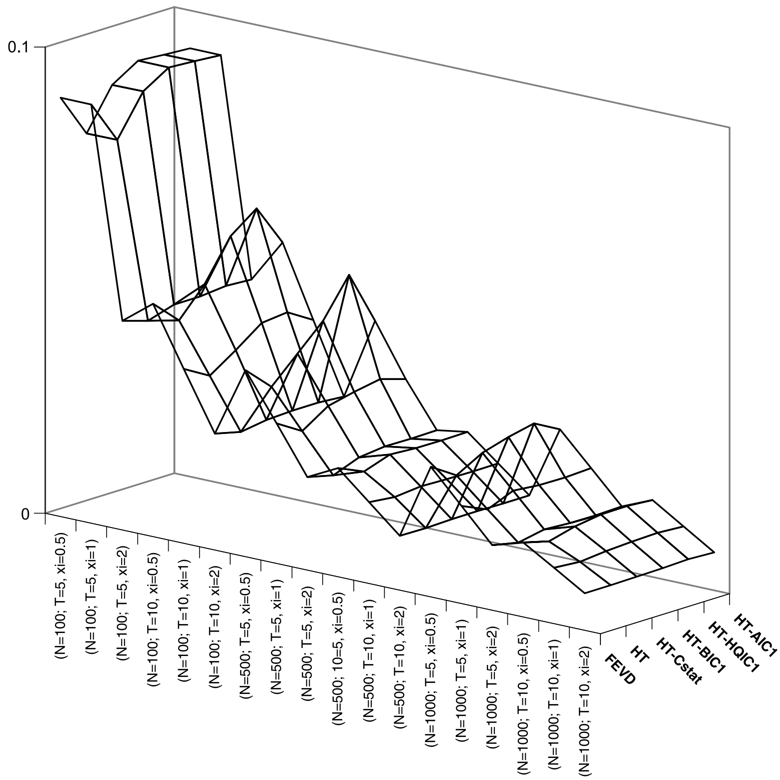

Fig. 6.5 NORMSQD surface plot for time-varying variables in MC simulations

significantly deteriorate the estimators' performance in terms of bias and rmse. This holds in particular for the search-algorithm-based HT models and comes close to findings in Baltagi et al. (2003), who find that for small values of ξ, their proposed pretest estimator wrongly reverts to the REM specification although the underlying data structure implies a correlation of right-hand-side variables with the individual effects in the sense of a HT world.

Turning to the NORMAD and NORMSQD values for the time-fixed regressors, Figs. 6.6 and 6.7 show that average bias and rmse are roughly constant over different combinations in the time and cross-section dimension of the data, where the smallest bias is obtained from the standard HT model with perfect knowledge about the underlying variable correlation. On average, the bias of the FEVD is significantly higher than for the standard HT. Also, the performance of the algorithm based HT models is rather poor. In contrast, the NORMSQD values for the FEVD are rather small in contrast to the HT specifications, especially for small sample settings. The high NOMRSQD for HT models with imperfect knowledge about the underlying variable correlation can be explained by the above identified duality problem of this statistical approach. The standard HT model also suffers from small sample inefficiency but comes close to the FEVD benchmark for a larger sample sizes.

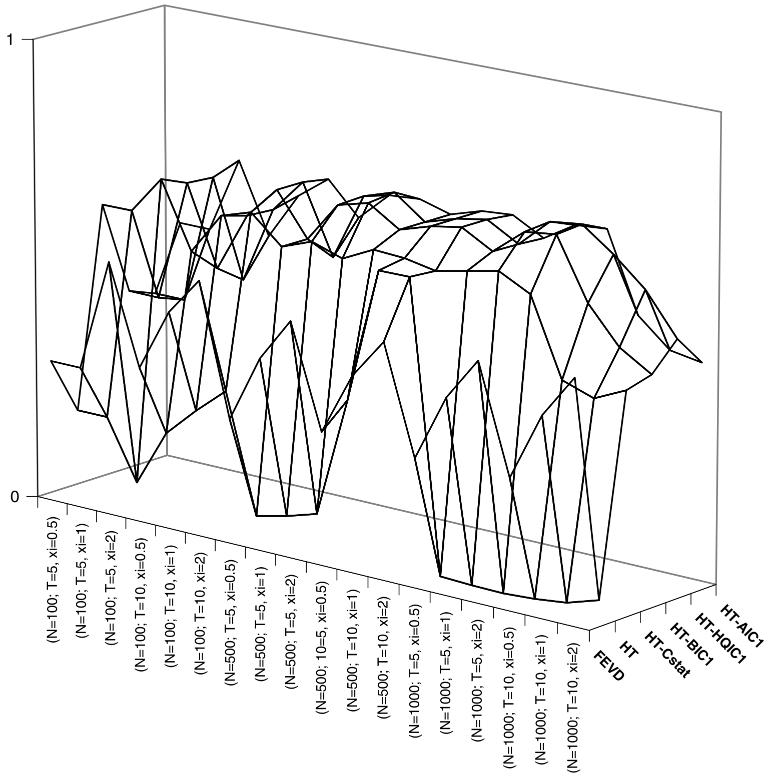

Fig. 6.6 NOMAD surface plot for time-fixed variables in MC simulations

6.4 Empirical Illustration: Trade Estimates for German Regions

Given the above findings from our Monte Carlo simulation experiment, in this section we aim to consider the empirical performance of the FEVD and HT model in an empirical application by estimating gravity type models. We take up the research question in Alecke et al. (2003, 2010) and specify trade equations for regional units. In particular, we aim to estimate gravity models for export flows among German states (NUTS1-level) and its EU27 trading partners using data for the period 1993–2005. We are particularly interested in quantifying the effects of time-fixed variables including geographical distance as a general proxy for trading costs as well as a set time-fixed binary dummies for border regions, the East German states as well as the specific trade pattern with the CEEC countries.[10] Earlier evidence in Belke and Spies (2008) for European data has shown that there is a considerable degree of het-

[10]The CEEC aggregate includes Hungary, Poland, the Czech Republic, Slovakia, Slovenia, Estonia, Latvia, Lithuania, Romania and Bulgaria.

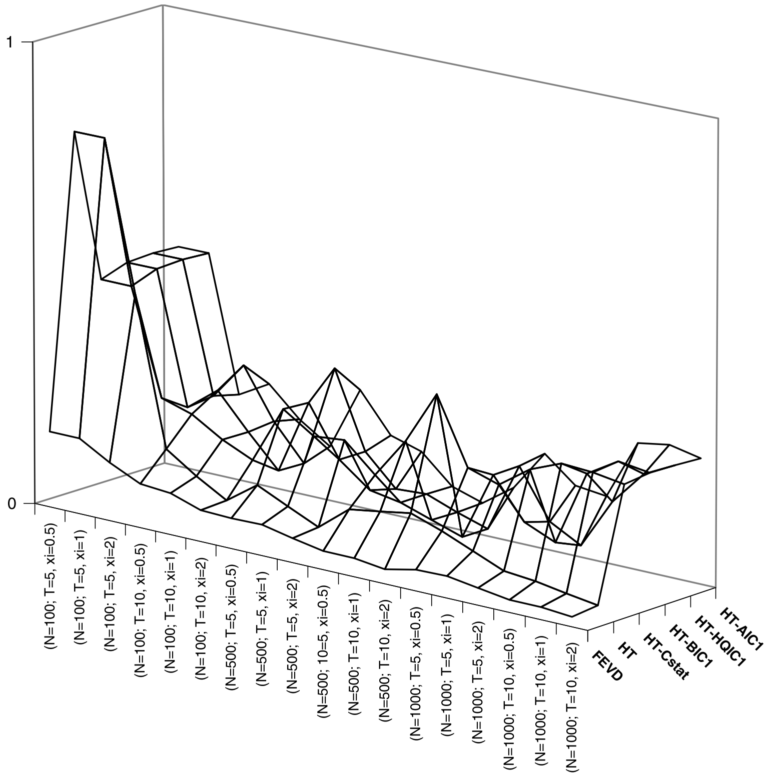

Fig. 6.7 NORMSQD surface plot for time-fixed variables in MC simulations

erogeneity for these time-fixed variables among different estimators. The empirical export model has the following form[11]

$$
\begin{aligned}
\log(EX_{ijt}) = \alpha_0 + \alpha_1 \log(GDP_{it}) + \alpha_2 \log(POP_{it}) + \alpha_3 \log(GPD_{jt}) \\
+ \alpha_4 \log(POP_{jt}) + \alpha_5 \log(PROD_{it}) + \alpha_6 \log(DIST_{ij}) + \alpha_7 SIM \\
+ \alpha_8 RLF + \alpha_9 EMU + \alpha_{10} EAST + \alpha_{11} BORDER + \alpha_{12} CEEC, \quad (6.7)
\end{aligned}
$$

where the index indicates German regional exports from region i to country j for time period t and imports to German state i from country j respectively. The variables in the model are defined as follows[12]

- EX = Export flows from region i to country j
- GDP = Gross domestic product in i and j respectively
- POP = Population in i and j

[11] Results for an import equation with qualitatively similar results can be obtained from the author upon request.

[12] Further details can be found in the data Appendix B in Table 6.3.

- $PROD$ = Labor productivity in i and j
- $DIST$ = Geographical distance between state/national capitals
- SIM = Similarity index defined as: $\log(1 - (\frac{GDP_{i,t}}{GDP_{i,t}+GDP_{j,t}})^2 - (\frac{GDP_{j,t}}{GDP_{i,t}+GDP_{j,t}})^2)$
- RLF = Relative factor endowments in i and j defined as: $\log|(\frac{GDP_{i,t}}{POP_{i,t}}) - (\frac{GDP_{j,t}}{POP_{j,t}})|$
- EMU = EMU membership dummy for i and j
- $EAST$ = East German state dummy for i
- $BORDER$ = Border region dummy between i and j
- $CEEC$ = CEE country dummy for j

The estimation results are shown in Table 6.2. We particularly focus on the FEVD and HT estimates for the variable $\log(DIST_{ij})$ as well as the time-fixed dummies *EAST*, *BORDER* and *CEEC*. The HT approach rests on the C-statistic-based downward-testing approach to find a consistent set of moment conditions.

In line with our Monte Carlo simulations, both the FEVD and HT estimators are very close in quantifying the time-varying variables in the gravity model for Ger-

Table 6.2 Gravity model for EU wide export flows for German states (NUTS1 level)

$Log(EX)$	POLS	REM	FEM	FEVD	HT$^{\$}$
$Log(GDP_i)$	1.04***	0.35*	0.83**	0.83***	0.87***
	(0.135)	(0.034)	(0.273)	(0.273)$^{\#}$	(0.271)
$Log(GDP_j)$	0.64***	0.31***	0.34***	0.34**	0.35***
	(0.026)	(0.034)	(0.044)	(0.044)$^{\#}$	(0.043)
$Log(POP_i)$	0.03	0.69***	−1.38***	−1.38**	0.18
	(0.132)	(0.197)	(0.398)	(0.398)$^{\#}$	(0.263)
$Log(POP_j)$	0.19***	0.48***	1.79***	1.79***	0.38***
	(0.025)	(0.041)	(0.302)	(0.302)$^{\#}$	(0.084)
$Log(PROD_i)$	−0.15	2.11***	1.48***	1.48***	1.76***
	(0.241)	(0.228)	(0.275)	(0.275)$^{\#}$	(0.268)
$Log(DIST_{ij})$	−0.87***	−1.04***	(dropped)	−0.97***	−1.73***
	(0.021)	(0.052)		(0.021)$^{\#}$	(0.403)
SIM	−0.03***	−0.17***	−0.18***	−0.18***	−0.29***
	(0.011)	(0.052)	(0.062)	(0.048)$^{\#}$	(0.039)
RLF	0.01	0.03***	0.03***	0.03	0.03***
	(0.011)	(0.008)	(0.008)	(0.044)$^{\#}$	(0.007)
EMU	0.45***	0.36***	0.31***	0.31***	0.34***
	(0.029)	(0.019)	(0.021)	(0.054)$^{\#}$	(0.019)
$EAST$	−0.80***	−0.38***	(dropped)	−1.03***	−0.26**
	(0.039)	(0.075)		(0.043)$^{\#}$	(0.110)
$BORDER$	0.28***	0.26*	(dropped)	0.07***	−0.38
	(0.050)	(0.150)		(0.008)$^{\#}$	(0.438)
$CEEC$	0.47***	−0.20**	(dropped)	0.93***	−0.22*
	(0.055)	(0.086)		(0.063)$^{\#}$	(0.131)

(*continued on the next page*)

Table 6.2 (Continued)

Log(*EX*)	POLS	REM	FEM	FEVD	HT$
No. of obs.	4784	4784	4784	4784	4784
No. of groups		368	368	368	368
Time effects		yes	yes	yes	yes
Wald test (p-val.)		(0.00)	(0.00)	(0.00)	(0.00)
p-value of BP LM (POLS/REM)		0.00			
p-value of F-test (POLS/FEM)			0.00		
Hausman m-stat.			147.2		
(REM/FEM)			(0.00)		
DWH endogeneity test					25.14
(p-value)					(0.00)
Sargan overid. test					6.25
(p-value)					(0.05)
C-statistic for $Dist_{ij}$					14.12
(p-value)					(0.00)
Pagan–Hall IV het.test					35.9
(p-value)					(0.10)

Note: Standard errors are robust to heteroskedasticity
*Denote statistical significance at the 10% level **Denote statistical significance at the 5% level ***Denote statistical significance at the 1% level #Corrected SEs for the FEVD estimator based on the *xtfevd* Stata routine provided by Plümper and Tröger (2007) $Using the C-statistic based downward testing algorithm with group means of $X1 = [GDP_{j,t}, POP_{i,t}, RLF_{ij,t}]$ as IVs for $Z2 = [DIST_{ij}]$

man regional export activity. As expected from its theoretical foundation (see e.g. Egger 2000; Feenstra 2004), both home and foreign country GDP have a positive and significant influence on German export activity, indicating that trade increases with absolute higher income levels. Moreover, home region productivity (defined as GDP per total employment) is also found to be statistically significant and highly positive, which in turn can be interpreted in line with recent findings based on firm-level data (see, e.g., Helpman et al. 2003, or Arnold and Hussinger 2006, for the German case) that the degree of internationalization of home firms (both trade and FDI) increases with higher productivity levels. The interpretation of the population variable in the gravity model is less clear cut. Both the FEVD and HT estimator find a positive coefficient sign for foreign population, which can be interpreted in favor of the market potential approach indicating that German export flows are higher for population-intense economies. Also, for the GDP based interaction variable *SIM* (definition see above), the two estimators show similar results.

However, as already observed throughout the Monte Carlo simulation experiment for the time-fixed variables, the estimators show a considerable degree of heterogeneity. In our export model, the C-statistic-based HT approach finds a coefficient for the distance variable (-1.73) that is almost twice as large as the respective coefficient in the POLS, REM and FEVD (-0.97) case. A similar difference between

FEVD and HT model results were also found in Belke and Spies (2008) for EU wide data (the authors report coefficients for the distance variable in the HT case as -1.83 compared to -1.39 in the FEVD case). Without the additional knowledge from the above Monte Carlo simulation experiment, we could hardly answer the question whether this discrepancy among estimators either indicates an upward bias of the HT model given the fact that (for national data) the parameter estimate for the distance variable typically ranges between -0.9 to -1.3 (see, e.g., Disdier and Head 2008 as well as Linders 2005) or whether the use of smaller regional entities serves as a better proxy for geographical distance thus gives a more accurate estimate for trade costs (which may be possibly higher).

However, in the light of the Monte Carlo simulation results together with the typical range of national estimates, it seems plausible to rely on the FEVD estimation results, although the HT model passes the Hansen/Sargan overidentification test (treating geographical distance as correlated with the unobserved individual effects). Also, for the further time-fixed dummy variables in the model the FEVD estimates show more reliable coefficient signs than the HT model: That is, we would expect the border dummy to be positive as, e.g., found in Lafourcade and Paluzie (2005) for European border regions. Also, German-CEEC trade was persistently found to be above its ‘potential’ in earlier studies (such as Schumacher and Trübswetter 2000; Buch and Piazolo 2000; Jakab et al. 2001; Caetano et al. 2002 as well as Caetano and Galleg 2003). In both cases, the FEVD estimates are thus more in line with recent empirical findings than the HT instrumental variable estimation.

6.5 Conclusion

In this chapter, we have performed a Monte Carlo simulation experiment supported by an empirical illustration to compare the empirical performance of IV and non-IV estimators for a regression setup, which includes time-fixed variables as right-hand-side regressors and where endogeneity matters. We define the latter as any correlation between the explanatory variables with the model’s error term. In specifying empirical estimators, we focus on the Hausman–Taylor (1981) IV model both with perfect and imperfect knowledge about the underlying variable correlation with the model’s residuals and non-IV two-step estimators such as the fixed effects vector decomposition (FEVD) model recently proposed by Plümper and Tröger (2007). Our results show that the HT (with perfect knowledge) works better for time-varying, while the FEVD for time-fixed variables. Averaging over all parameters, we find that the HT model (with perfect knowledge) generally has the smallest bias, while the FEVD shows by far the lowest root mean square error (rmse) as a general efficiency measure. Especially in small sample settings, our Monte Carlo simulations show that the IV-based HT model has a large standard deviation around the unbiased point estimate.

Additionally, relaxing the assumption of perfect knowledge for the HT model, the empirical performance of the latter significantly worsens. We compute different algorithms to select consistent IV sets centering on the Hansen/Sargan overidentification test (J-statistic). However, all estimates based on these algorithms generally show a much weaker empirical performance than the non-IV alternative (FEVD). One major drawback of the HT models with imperfect knowledge is a 'duality' problem in small-sample settings, where the estimator has difficulties to discriminate between consistent and inconsistent moment condition vectors. Our Monte Carlo experiment shows that for the HT model, one should have good theoretical arguments for proper instrument choice rather than using solely statistical criteria for IV selection. An alternative choice for the applied researcher are non-IV two-step estimators such as the FEVD proposed by Plümper and Tröger (2007), which show an on average acceptable performance in our Monte Carlo simulations and yield plausible results for the estimation of German regional trade flows using gravity-type models. The results highlight the delicate choice of an appropriate estimator for applied researchers, aiming to quantify the effect of policy relevant variables such as trade costs.

Appendix A: Monte Carlo Simulation Design

The starting point for the Monte Carlo simulation experiment is (6.4). The time-varying regressors $x_{1_1}, x_{1_2}, x_{2_1}, x_{2_2}$ are generated by the following autoregressive process:

$$x_{n_m,i,t=1} = 0 \quad \text{with } n, m = 1, 2, \tag{6.8}$$

$$x_{1_1,i,t} = \rho_1 x1_{i,t-1} + \delta_i + \xi_{i,t} \qquad \text{for } t = 2, \ldots, T, \tag{6.9}$$

$$x_{1_2,i,t} = \rho_2 x2_{i,t-1} + \psi_i + \omega_{i,t} \qquad \text{for } t = 2, \ldots, T, \tag{6.10}$$

$$x_{2_1,i,t} = \rho_3 x3_{i,t-1} + \mu_i + \tau_{i,t} \qquad \text{for } t = 2, \ldots, T, \tag{6.11}$$

$$x_{2_2,i,t} = \rho_4 x4_{i,t-1} + \mu_i + \lambda_{i,t} \qquad \text{for } t = 2, \ldots, T. \tag{6.12}$$

For the time-fixed regressors $z_{1_1}, z_{1_2}, z_{2_1}$ we analogously define

$$z_{1_1,i} = 1, \tag{6.13}$$

$$z_{1_2,i} = g_1 \psi_i + g_2 \delta_i + \kappa_i, \tag{6.14}$$

$$z_{2_1,i} = \mu_i + \delta_i + \psi_i + \epsilon_i. \tag{6.15}$$

The variable $z_{1_1,i}$ simplifies to a constant term, $z_{2_1,i}$ is the endogenous time-fixed regressor since it contains μ_i as right-hand-side variable, the weights g_1 and g_1 in the specification of $z_{1_2,i}$ control for the degree of correlation with the time-varying variables $x_{1_1,i,t}$ and $x_{1_2,i,t}$.[13] The remainder innovations in the data generating process are defined as follows:

$$\nu_{i,t} \sim N(0, \sigma_\nu^2), \tag{6.16}$$

$$\mu_i \sim N(0, \sigma_\mu^2), \tag{6.17}$$

[13]We vary g_1 and g_2 on the interval $[-2, 2]$. The default is $g_1 = g_2 = 2$.

$$\delta_i \sim U(-2,2), \tag{6.18}$$

$$\xi_{i,t} \sim U(-2,2), \tag{6.19}$$

$$\psi_i \sim U(-2,2), \tag{6.20}$$

$$\omega_{i,t} \sim U(-2,2), \tag{6.21}$$

$$\tau_{i,t} \sim U(-2,2), \tag{6.22}$$

$$\lambda_{i,t} \sim U(-2,2), \tag{6.23}$$

$$\epsilon_i \sim U(-2,2), \tag{6.24}$$

$$\kappa_i \sim U(-2,2). \tag{6.25}$$

Except μ_i and $\nu_{i,t}$, which are drawn from a normal distribution with zero mean and variance σ_μ^2 and σ_ν^2, respectively, all innovations are uniform on $[-2,2]$. For $\mu_i, \delta_i, \psi_i, \epsilon_i, \kappa_i$ the first observation is fixed over T. With respect to the main parameter settings in the Monte Carlo simulation experiment we set:

- $\beta_{1_1} = \beta_{1_2} = \beta_{2_1} = \beta_{2_2} = 1$
- $\gamma_{1_2} = \gamma_{2_1} = 1$
- $\rho_1 = \rho_2 = \rho_3 = \rho_4 = 0.7$

All variable coefficients are normalized to one, the specification of $\rho < 1$ assures that the time-varying variables are stationary. We also normalize σ_ν equal to one and define a load factor ξ determining the ratio of the variance terms of the error components as $\xi = \sigma_\mu/\sigma_\nu$. ξ takes values of (2, 1 and 0.5). We run simulations with different combinations in the time and cross-section dimension of the panel as $N = (100, 500, 1000)$ and $T = (5, 10)$. All Monte Carlo simulations are conducted with 500 replications for each permutation in y and u. As in Arellano and Bond (1991) we set $T = T + 10$ and cut off first 10 cross-sections, which gives a total sample size of NT observations.

We apply the FEVD and Hausman–Taylor estimators.[14] As outlined above, one drawback in earlier Monte Carlo based comparisons between the HT model and rival non-IV candidates was the strong assumption made for IV selection in the HT case, namely that true correlation between right-hand-side variables and the error term is known. However, this may not reflect the identification and estimation problem in applied econometric work and Alfaro (2006) identifies it as one of the open questions for future investigation in Monte Carlo simulations. We therefore account for the HT variable classification problem by implementing algorithms from 'model selection criteria'-literature, which combine information from Hansen/Sargan overidentification test for moment condition selection as outlined above and time-series information-criteria. Following Andrews (1999), we define a general model selection criteria (MSC) based on IV estimation as

$$MSC_n(m) = J(m) - h(c)k_n, \tag{6.26}$$

[14] For the FEVD estimator, we employ the Stata routine *xtfevd* written by Plümper and Tröger (2007), the HT model is implemented using the user written Stata routine *ivreg2* by Baum et al. (2003).

where n is the sample size, c as number of moment conditions selected by model m based on the Hansen J-statistic $J(m)$, $h(.)$ is a general function, k_n is a constant term. As (6.26) shows, the model selection criteria centers around the J-statistic.[15] The second part in (6.26) defines a 'bonus' term rewarding models with more moment conditions, where the form of function $h(.)$ and the constant terms k_n are specified by the researcher. For empirical application Andrews (1999) proposes three operationalizations in analogy to model selection criteria from time series analysis:

- MSC-BIC: $J(m) - (k - g)\ln n$
- MSC-AIC: $J(m) - 2(k - g)$
- MSC-HQIC: $J(m) - Q(k - g)\ln\ln n$ with $Q = 2.01$

where $(k - g)$ is the number of overidentifying restrictions, and depending on the form of the bonus term, the MSC may take the BIC (Bayesian), AIC (Akaike) and HQIC (Hannan Quinn) form. We apply all three information criteria in the Monte Carlo simulations motivated by the results in Andrews and Lu (2001) and Hong et al. (2003) that the superiority of one of the criteria over the others in terms of finding consistent moment conditions may vary with the sample size.[16] For each of these MSC criteria, we specify the following algorithms:

1. Unrestricted form: For all possible IV combinations out of the full IV-set $S = (QX1, QX2, PX1, PX2, Z1, Z2)$, where Q denote deviations from group means and P are group means. The IV set satisfies the order condition $k_1 > g_2$ (giving a total number of 42 combinations). We calculate the value of the MSC criterion (for the BIC, AIC and HQIC separately) and choose that model as final HT specification, which has minimum MSC value over all candidates.
2. Restricted form: This algorithm follows the basic logic from above, but additionally puts the further restriction that only those models serves as MSC candidates for which the p-value of the J-statistic is a above a critical value $K_{crit.}$, which we set to 0.05 to maximize the likelihood that the selected moment conditions are valid in terms of statistical pre-testing. The restricted (see Andrews 1999, for this point).

We present flow charts of the restricted and unrestricted MSC based search algorithm in Fig. 6.8. As Andrews (1999) argues, the above specified model selection criteria is closely related to the C-statistic approach by Eichenbaum et al. (1988) to test whether a given subset of moment conditions is correct or not.[17]

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[15] A detailed description of different moment selection criteria is given in a longer working paper version of this paper, see Mitze 2009.

[16] Generally, the MSC-BIC criterion is found to have the best empirical performance in large samples, while the MSC-AIC outranks the other criteria in small sample settings, but performs poor otherwise.

[17] The C-statistic can be derived as the difference of two Hansen/Sargan overidentification tests with $C = J - J_1 \sim \chi^2(M - M_1)$, where M_1 is the number of instruments in S_1 and M is the total number of IVs.

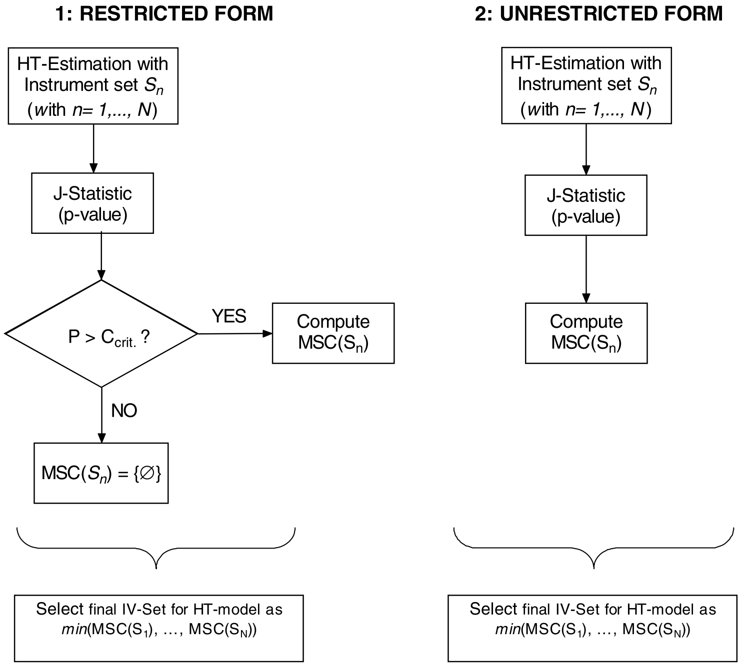

Fig. 6.8 MSC based model selection algorithm for HT-approach

Thus, alternatively to the above described algorithms, we specify a downward-testing approach based on the C-statistic: Here, we start from the HT model with full IV set in terms of the REM moment conditions as $S_1 = (QX1, QX2, PX1, PX2, Z1, Z2)$. We calculate the value of the J-statistic for the model with IV-set S_1 and compare its p-value with a predefined critical value $K_{crit.}$, which we set in line with the above algorithm as $K_{crit.} = 0.05$. If $P_{S_1} > K_{crit.}$ we take this model as a valid representation in terms of the underlying moment conditions. If not, we calculate the value of the C-statistic for each single instrument in S_1 and exclude that instrument from the IV-set that has the maximum value of the C-statistic.

We then re-estimate the model based on the IV-subset S_2 net of the selected instrument with the highest C-statistic and again calculate the J-statistic and its respective p-value. If $P_{S_2} > K_{crit.}$ is true, we take the HT-model with S_2 as final specification and otherwise again calculate the C-statistic for each instrument to exclude that one with the highest value. We run this downward-testing algorithm for moment conditions until we find a model that satisfies $P_{S_.} > C_{crit.}$ or, at the most, until we reach the IV-sets S_n to S_m, where the number of overidentifying restrictions $(k - g) = 1$, since the J-statistic is not defined for just-identified models. Out of S_n to S_m, we then pick the model with the lowest J-statistic value. The C-statistic based model selection algorithms is graphically summarized in Fig. 6.9.

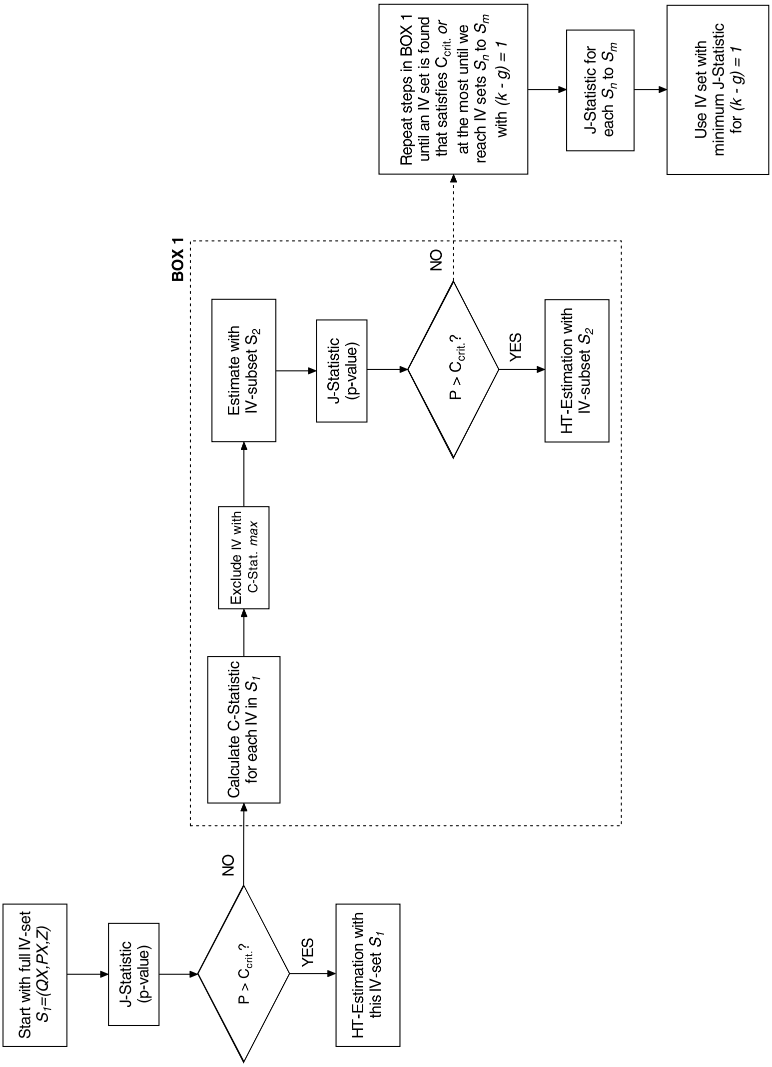

Fig. 6.9 *C*-statistic based model selection algorithm for HT-approach

Appendix B: Variable Description for the Gravity Model

Table 6.3 Data description and source for export model

Variable	Description	Source
EX_{ijt}	Export volume, nominal values, in Mio. €	Destatis (2008)
GDP_{it}	Gross domestic product, nominal values, in Mio. €	VGR der Länder (VGRdL 2008)
GDP_{jt}	Gross domestic product, nominal values, in Mio. €	Eurostat (2008)
POP_{it}	Population, in 1000	VGRdL
POP_{jt}	Population, in 1000	Groningen Growth & Development center (GGDC 2008)
SIM_{ijt}	$SIM = \log\left(1 - \left(\frac{GDP_{it}}{GDP_{it}+GDP_{jt}}\right)^2 - \left(\frac{GDP_{jt}}{GDP_{it}+GDP_{jt}}\right)^2\right)$	see above
RLF_{ijt}	$RLF = \log\left\lvert\left(\frac{GDP_{it}}{POP_{it}}\right) - \left(\frac{GDP_{jt}}{POP_{jt}}\right)\right\rvert$	see above
EMP_{it}	Employment, in 1000	VGRdL
EMP_{jt}	Employment, in 1000	EU Commission (2008)
$PROD_{it}$	$Prod_{it} = \left(\frac{GDP_{it}}{EMP_{it}}\right)$	see above
$PROD_{jt}$	$Prod_{jt} = \left(\frac{GDP_{jt}}{EMP_{jt}}\right)$	see above
$DIST_{ij}$	Distance between state capital for Germany and national capital for the EU27 countries, in km	Calculation based on coordinates, obtained from www.koordinaten.de
EMU	(0, 1)-dummy variable for EMU members since 1999	
$EAST$	(0, 1)-dummy variable for the East German states	
$CEEC$	(0, 1)-dummy variable for the Central and Eastern European countries	
$BORDER$	(0, 1)-dummy variable for country pairs with a common border	

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Chapter 7
Within and Between Panel Cointegration in the German Regional Output–Trade–FDI Nexus

7.1 Introduction

The relationship between economic growth and internationalization activity is an active field of economic research at the firm, regional and national levels. Two of the central transmission channels through which trade and international investment activity (the latter typically in the form of Foreign Direct Investment, henceforth FDI) may affect economic growth and development are the existence of technological diffusion via spillovers and the exploitation of market-size effects. While the latter mechanism is closely related to the classical work on 'export-led-growth' in the field of trade theory and regional economics (see, e.g., Hirschman 1958), the importance of technological diffusion and spillover effects has been particularly emphasized in the new growth theory (see, e.g., Barro and Sala-i-Martin 2004, for an overview).

In seminal papers, Romer and Rivera-Batiz (1991) as well as Rivera-Batiz and Xie (1993) already hinted at the importance of knowledge spillovers in generating permanent growth effects from trade opening, while Feenstra (1990) demonstrated that, without technological diffusion, an economy will experience a decline of its growth rate after liberalizing trade. Summarizing the findings of the theoretical literature dealing with the spatial distribution of growth related to trade openness, Tondl (2001) argues that perfect integration with trade liberalization and technology diffusion may spur growth and eventually lead to income convergence among the group of participating regions/countries in an endogenous growth world. However, for the medium run, imperfect integration may lead to growth divergence or convergence among different 'clubs'. In this sense, it may be important to account for potentially different short- and long-run effects of trade on growth in a more complex empirical modelling framework.

The likely uneven evolution of economic growth due to internationalization activity across time and space is also prominently discussed within the field of new economic geography (NEG). Long-run spatial divergence may be the result of a concentration of economic activity in certain agglomerations. In almost all NEG models, free trade and capital movement play a key role. Whether agglomeration or dispersion forces dominate depends crucially on the underlying core–periphery

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pattern as well as the impact of trade liberalization on the reduction of the transaction costs and the size of agglomeration effects such as market size and economies of scale. Especially for FDI, the latter size factors are identified as key determinants across space rather than differences in saving rates as typically specified in the standard Solow model of growth. The latter neoclassical transmission channel is assumed to solely operate via capital accumulation, which takes place across space, when the capital-to-labor ratio is low and marginal products from capital investment are high. While the Solow model predicts (conditional) convergence, for models driven by market potential and increasing economies of scale, Martin and Ottaviano (1996) as well as Baldwin et al. (1998) show that along the lines of the new economic geography and growth models there might be a long-term equilibrium, which exhibits an asymmetric (divergent) location pattern.

As the discussion above shows, the interplay between economic growth and internationalization activity is a complex issue both across time and space. It is rather difficult to derive clear-cut results, given the plurality of different approaches. In this chapter, we thus tackle this issue at the empirical level by analyzing the growth–trade–FDI nexus for West German federal states (NUTS1 Level) for the period 1976–2005. Our methodological approach rests on the analysis of merging the long- and short-run perspective by means of cointegration analysis, which aims to identify co-movements of the variables within and between cross-sections. The notion of a global panel cointegration approach has been recently introduced by Beenstock and Felsenstein (2010). This framework allows us to specify spatial panel error correction models (SpECM) which are able to identify short- and long-run co-movements of the variables in focus and avoid any bias stemming from spurious regressions.

From a statistical point of view, a proper handling of variables that may contain unit roots in the time dimension is of vital importance.[1] The merit of the global cointegration approach is that it aims at analyzing the consequences of spatial effects for the time series behavior of variables. That is, consider the case of two regions of which one region is heavily engaged in international trade or FDI and directly benefits from this activity in terms of output growth, e.g. through the exploitation of market potentials and technological diffusion. The second region instead is not actively engaged in trade activity but benefits from the first region's openness via forward and backward linkages, which in turn raise output for the second region, too. Thus, rather than having a stable long-run co-movement between its own level of internationalization activity and output evolution, the inclusion of a spatially lagged trade variable is needed to ensure cointegration of the second region's output level with trade and FDI activity. Moreover, apart from the importance of spatial lags in finding stable cointegration relationships for output, trade, and FDI in a time-series perspective, the method may also help to control for any cross-sectional dependence in the long- and short-run specification of the SpECM.

The remainder of the chapter is organized as follows. In the next section, we give a brief overview of recent empirical contributions regarding the relationship of

[1] Note that this analysis does not address the handling of variables containing spatial unit roots in the definition of Fingleton (1999).

economic growth, trade, and international capital movement. So far, the empirical literature has focused on the time-series perspective, aiming at identifying cointegration relationships and analyzing the direction of causality among the variables involved. Opening up the field of research to an explicit account of space may add further insights. Section 7.3 then briefly discusses the database used and presents some stylized facts at the German regional level. Section 7.4 presents the econometric specification used and, in Sect. 7.5, we report the main estimation results for our chosen SpECM modelling framework. Section 7.6 performs a robustness check with an alternative spatial weighting matrix, Sect. 7.7 concludes the chapter.

7.2 Theory and Empirics of Output–Trade–FDI Linkages

As already sketched above, there are various approaches in order to motivate the link between output determination and internationalization activity at the regional level. To elaborate different testable hypothesis, in the conduct of this chapter we start from export-base driven theoretical models (see, e.g., McCann 2001, for an overview).[2] According to the export base approach, regional output determination is mainly driven by its internationalization activity given that the regional private and public consumption level is limited to a certain amount. In contrast, foreign demand for regional products does not face these capacity constraints. Regional agents have then to decide about how to serve foreign demands, either by means of export or FDI activity. As argued above, next to this direct link between internationalization activity and regional output, the latter may also be determined by indirect spatial spillovers given that intranational input–output relationships exist. A stylized output function can then be written as

$$Y_t = f(FDI_t, TR_t, FDI_t^*, TR_t^*, \mathbf{Z}), \tag{7.1}$$

where Y_t denotes the aggregate production of the economy at time t as a function of internationalization activity in terms of *FDI* and Trade (*TR*), where "*" indicate variables measuring spatial spillovers. Details on how to construct such spatial lag variables are given in Sect. 7.4. $\mathbf{Z}$ is a vector of further domestic determinants of the region's output level. We use this augmented export base framework as a starting point for our empirical model specification with theoretically motivated variable selection. At the empirical level, many studies have already hinted at the strong correlation among these variables either in a pairwise or more general testing approach. In a recent survey dealing with the FDI-growth relationship, the OECD (2002) finds for 11 out of 14 studies that FDI contributes positively to income growth and factor productivity. A further meta-analysis of the latter literature is also presented by Ozturk (2007). The author likewise concludes that most studies find a positive effect of FDI on growth.

[2] An alternative starting point would be the specification of an aggregate production function framework, which is particularly useful to highlight the link between internationalization activity and technology growth (see, e.g., Edwards 1998).

Investigating the simultaneous interference of trade and FDI on growth and vice versa, Ekanayake et al. (2003), Dritsaki et al. (2004), Wang et al. (2004), Makki and Somwaru (2004) as well as Hansen and Rand (2006) among others use cointegration analysis to identify the long- and short-run effects among the variables and, by means of Granger causality tests, get general evidence for a bi-directional causal relationship between internationalization activity and economic growth. Using data for North and South American countries between 1960 and 2001 (including Brazil, Canada, Chile, Mexico, and USA), Ekanayake et al. (2003), for instance, report evidence in favor of trade-led growth, while results for (inward) FDI-led growth are mixed. For a panel of 79 countries, Wang et al. (2004) report that FDI has a positive impact on growth in high- and middle-income countries, but not in low-income countries. Looking closer at a subsample of developing countries, Hansen and Rand (2006) find that FDI has an impact on GDP via knowledge transfers and the adoption of new technology.

Only very few studies give an explicit account of spatially related variables in the analysis of the trade–FDI–growth nexus. One exception is Ozyurt (2008), who estimates a long-run model for labor productivity of Chinese provinces driven by trade and FDI as well as their respective spatial lags.[3] The author finds that FDI and trade volumes have a positive direct effect on labor productivity. The results for the sample period 1979–2006 show that the geographical environment has a subsequent influence on labor productivity in a certain region. Besides the spatial lag of the endogenous variable as a 'catch-all' proxy for spatial effects, FDI spillovers turn out to be of specific interregional nature. These findings give a first indication that spillovers from internationalization activity are not restricted to a direct effect, but may also influence the economic development of neighboring regions.

The above sketched literature gives rise to a set of testable hypotheses, which can be summarized as follows:

- *Hypothesis* 1: Trade and FDI activities are directly related through market size and intraregional technological spillover effects to the economy's output performance both in the long- and short-run ('Trade-led' and 'FDI-led' growth).
- *Hypothesis* 2: Trade and FDI activities are indirectly related to the economy's output performance through forward and backward linkages as a source of interregional spillover effects both in the long- and short-run.
- *Hypothesis* 3: Besides trade and FDI spillovers, there are also direct short-run linkages between the economic growth performance of neighboring regions, which may stem from domestic rather than international sources.

The different direct and indirect transmission channels from internationalization activity for the stylized case of two regions are illustrated in Fig. 7.1. Solid arrows in the figure indicate a direct relationship between regional output and the region's internationalization activity, while dashed arrows mark indirect spatial spillover effects. The reader has to note that the reduction of the system to a single equation

[3] Additionally, there is a growing literature with respect to third-country effects of FDI activity. See, e.g., Baltagi et al. (2007).

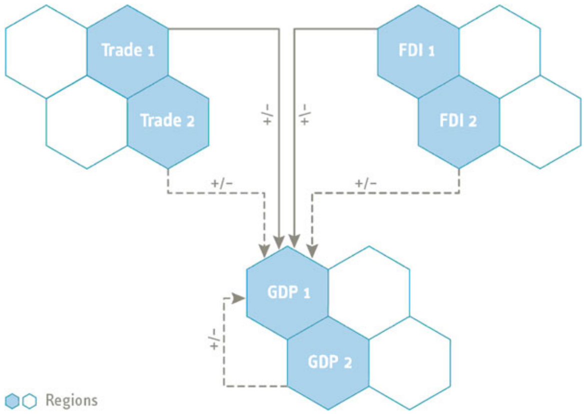

Fig. 7.1 Sources of internationalization effects on regional output

approach with causality being assumed to run from trade and FDI to growth abstracts from the likely role of feedback effects and bidirectional causality.

7.3 Data and Stylized Facts

For the empirical analysis, we use regional panel data for the 10 West German federal states between 1976 and 2005. Our data comprise GDP levels, export and import volumes, as well as inward and outward stocks of FDI. All data are used in real terms. For the analysis, all variables are transformed into logarithms.[4] As a benchmark we use a spatial weighting scheme that contains binary information on whether two states share a common border or not. The spatial weighting matrix is used in its row-normalized form. To check for the sensitivity of the results, we also use a weighting matrix based on interregional transport flows rather than geographical information. The sources and summary statistics of the data are given in Table 7.1. Additionally, Fig. 7.2 plots the time evolution of the variables for each West German federal state. As the figure shows, all variables increase over time. The evolution of real GDP shows the smoothest time trend, while the values for trade and FDI activities show a more volatile pattern. The figure also displays that both inward as outward FDI stocks start from a rather low level in the 1970s but increase rapidly over time. Except for the small states *Bremen* and *Saarland*, which show to have a strong trade performance, the gap between trade and FDI activity gradually decreases over time. In the following, we will more carefully account for the co-evolution of GDP and internationalization activity by means of cointegration analysis.

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[4]It would be desirable to have a higher degree of regional disaggregation rather than $N = 10$ with $T = 30$. However, no such data on trade and FDI activity is available. The panel structure of the data is nevertheless still comparable to Beenstock and Felsenstein (2010) with $N = 9$ and $T = 18$, so that it should be feasible to apply their proposed method to our regional data.

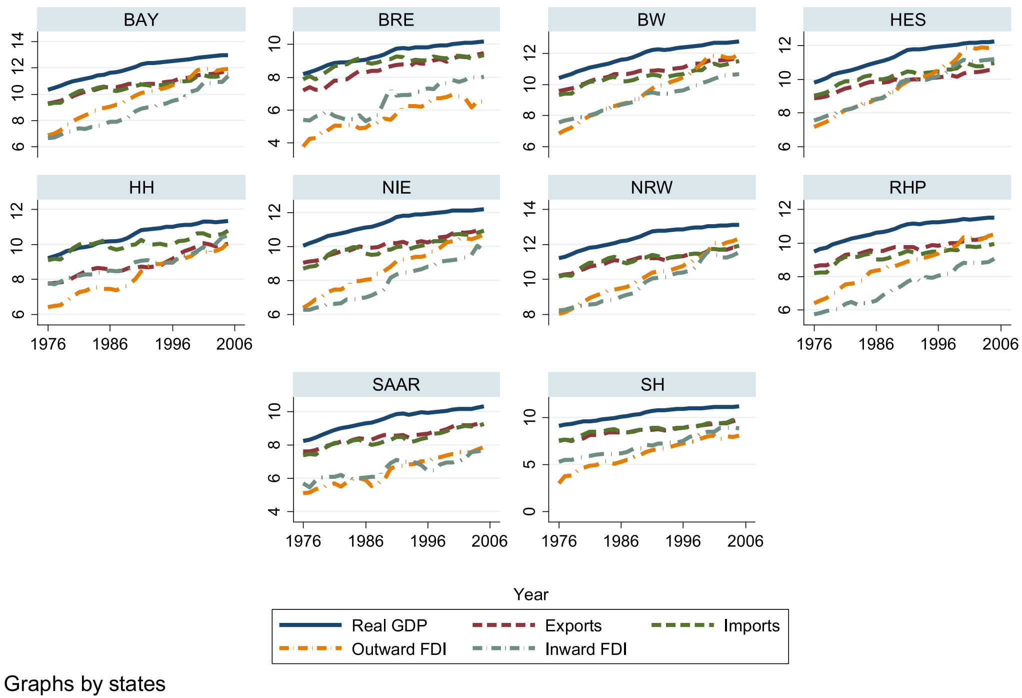

Fig. 7.2 GDP, trade and FDI by German states (in logs). *Source*: See Table 7.1. *Note*: BW = Baden Württemberg, BAY = Bavaria, BRE = Bremen, HH = Hamburg, HES = Hessen, NIE = Lower Saxony, NRW = North Rhine-Westphalia, RHP = Rhineland-Palatine, SAAR = Saarland, SH = Schleswig-Holstein

Table 7.1 Data sources and summary statistics of the variables

Variable	Description	Source	Obs.	In logarithms			
				Mean	Std. dev.	Min	Max
y	Real GDP (in Euro)	VGR der Länder (VGRdL 2009)	300	10.95	1.17	8.19	13.12
ex	Real exports (in Euro)	Destatis (2009)	300	9.66	1.12	7.19	11.9
im	Real imports (in Euro)	Destatis (2009)	300	9.76	1.01	7.37	11.93
fdi in	Real stock of inward FDI (in Euro)	Deutsche Bundesbank (2009)	300	8.16	1.57	5.3	11.57
fdi out	Real stock of outward FDI (in Euro)	Deutsche Bundesbank (2009)	300	8.32	2.03	3	12.36

Table 7.2 Panel unit root tests

Variable	IPS test for $N = 10$, $T = 30$			CADF test for $N = 10$, $T = 30$		
	W[t-bar]	p-value	Av. lags	Z[t-bar]	p-value	Av. lags
y	0.07	(0.53)	1.50	0.53	(0.70)	2
ex	-1.37^{*}	(0.09)	1.10	-1.16	(0.12)	1
im	2.69	(0.99)	0.50	-0.59	(0.28)	1
fdi in	0.56	(0.71)	1.20	-2.21^{**}	(0.02)	1
fdi out	-0.91	(0.18)	0.70	1.45	(0.93)	1
Δy	-9.27^{***}	(0.00)	1.10	-4.51^{***}	(0.00)	1
Δex	-13.52^{***}	(0.00)	0.70	-7.08^{***}	(0.00)	1
Δim	-9.85^{***}	(0.00)	0.70	-6.83^{***}	(0.00)	1
Δ*fdi in*	-13.58^{***}	(0.00)	0.70	-5.34^{***}	(0.00)	1
Δ*fdi out*	-9.81^{***}	(0.00)	0.90	-3.88^{***}	(0.00)	1

Note: For IPS, the optimal lag length is chosen according to the AIC. H_0 for both panel unit root test states that all series contain a unit root

*Denote statistical significance at the 10% level **Denote statistical significance at the 5% level

***Denote statistical significance at the 1% level

As we have seen from Fig. 7.2, all variables grow over time, indicating that the variables are likely to be non-stationary. To analyze this more in depth, we therefore compute standard panel unit root tests proposed by Im et al. (2003) as well as Pesaran (2007). The latter test has the advantage that it is more robust to cross-sectional correlation brought in by spatial dependence (see, e.g., Baltagi et al. 2007), while the Im et al. (2003) test is found to be oversized, when the spatial autocorrelation coefficient of the residual is large (around 0.8). The results of both panel unit root tests are reported in Table 7.2. As the results show, both test statistics give evidence that all variables are integrated of order I(1) and are stationary after taking first differences.

7.4 Econometric Specification

The estimation of $I(1)$-variables has a long tradition in time-series modelling and has recently been adapted to panel data econometrics (see, e.g., Hamilton 1994; Baltagi 2008). In this section, we expand the scope of the analysis from a within-panel perspective to a simultaneous account of between-panel linkages, leading to a more global concept of cointegration (see Beenstock and Felsenstein 2010). To show this, we start from a spatial panel data model with the following general long-run form:

$$Y_{it} = \alpha_i + \beta X_{it} + \theta Y_{it}^* + \delta X_{it}^* + u_{it}, \tag{7.2}$$

where Y_{it} is the dependent variable of the model for $i = 1, 2, \ldots, N$ spatial cross-sections, $t = 1, 2, \ldots, T$ is the time dimension of the model. X_{it} is a vector of exogenous control variables; α_i is a vector of cross-sectional fixed effects, and u_{it} is the model's residual term. Both Y and X are assumed to be time-integrated of order $Y \sim I(d)$ and $X \sim I(d)$ with $d \leq 1$. If X and Y are cointegrated, the error term u should be stationary as $u \sim I(0)$. Asterisked variables refer to spatial lags defined as

$$\begin{aligned} Y_{it}^* &= \sum_{j \neq i}^{N} w_{ij} Y_{jt}, \\ X_{it}^* &= \sum_{j \neq i}^{N} w_{ij} X_{jt}, \end{aligned} \tag{7.3}$$

where w_{ij} are typically row-standardized spatial weights with $\sum_j w_{ij} = 1$. As Beenstock and Felsenstein (2010) point out, in an aspatial specification u_{it} may be potentially affected by cross-sectional dependence. However, the presence of spatial lags should capture these effects and account for any bias stemming from omitted variables. Further, since the spatial lags Y_{it}^* and X_{it}^* are linear combinations of the underlying data, they have the same order of integration as Y_{it} and X_{it}, respectively. For the non-stationary case, the presence of spatial lags thus enlarges the cointegration space to find long-run specifications with a stationary residual term u_{it}.

As pointed out in the seminal work of Engle and Granger (1987), cointegration and error correction are mirror images of each other. We may thus move from the specification of the long-run equation in (7.2) to a dynamic specification in first differences, which nevertheless preserves the information of the long-run equation. The resulting (vector) error correction model ((V)ECM) describes the dynamic process through which cointegrated variables are driven in the adjustment process to their long-run equilibrium. In the following we build on the concept proposed by Beenstock and Felsenstein (2010) and specify a spatial ECM (SpECM) as dynamic process, in which spatially cointegrated variables co-move over time. We allow for deviations from a stable long-run equilibrium relationship in the short-run. However, the 'error correction' mechanism ensures the stability of the system in the long-run.

Therefore, the SpECM concept encompasses three important types of cointegration: (i) If cointegration only applies within spatial units but not between them, we refer to 'local' cointegration. The latter is the standard concept of cointegration with respect to (panel) time series analysis. (ii) 'Spatial' cointegration refers to the case in which non-stationary variables are cointegrated between spatial units but not within them. As Beenstock and Felsenstein (2010) point out, in this case, the long-term trends in spatial units are mutually determined and do not depend upon developments within spatial units. (iii) Finally, if nonstationary spatial panel data are both cointegrated within and between cross-sections, we refer to 'global' cointegration.

The resulting SpECM associated with (7.2) in its first-order form can be written:

$$\begin{aligned}\Delta Y_{it} = \gamma_{0i} + \gamma_1 \Delta Y_{it-1} + \gamma_2 \Delta X_{it-1} + \gamma_3 \Delta Y^*_{it-1} + \gamma_4 \Delta X^*_{it-1} \\ + \gamma_5 u_{it-1} + \gamma_6 u^*_{it-1} + e_{it},\end{aligned} \tag{7.4}$$

where e_{it} is the short-run residual which is assumed to be temporally uncorrelated, but might be spatially correlated such that $\mathrm{Cov}(e_{it}e_{jt}) = \sigma_{ij}$ is nonzero. The terms u_{it-1} and u^*_{it-1} are the (spatially weighted) residuals from the long-term relationships of the system. The latter are stationary for the case of a cointegration system. The coefficients for u and u^* can be interpreted as error correction coefficients, which drive the system to its long-run equilibrium state. Global error correction arises if γ_5 and γ_6 are non-zero. For the nested case of local cointegration, we typically assume that $\gamma_5 < 0$ in order to restore the long-run equilibrium.

It is straightforward to see that if the coefficients for u and u^* are zero, the long-run information used for estimation drops out and the system in (7.4) reduces to a single equation in a spatial VAR (SpVAR) formulation. Note, that in the short run, X may affect Y differently from how it affects Y in the long run. Hence, γ_2 in (7.4) may be different from δ in (7.2). It is also important to note that the coefficient for the time lag of the dependent variable (γ_1) is typically expected to have the same sign as the coefficient for u^* (γ_6), since the dynamics of Y will be affected by u^* among neighbors. For the case of $\gamma_5, \gamma_6 \neq 0$ the resulting SpECM specification exhibits 'global error correction'. As Beenstock and Felsenstein (2010) point out, the SpECM in (7.4) should only contain contemporaneous terms for ΔX and ΔX^* if credible instrument variables could be specified for them or if these variables are assumed to be exogenous. The latter implies for our empirical case, that error correction runs from X to Y but not the other way around.

7.5 Empirical Results

7.5.1 Within Panel Cointegration and ECM

In this section, we first start with the analysis of a aspatial model for output and internationalization activity as typically done in the empirical literature. We then test whether the inclusion of spatial lags improves our empirical model—both from a statistical as well economic perspective. As it has been shown in Table 7.2, all five variables are integrated time series. In order to use both the information in levels as well in first differences, the variables should be cointegrated to avoid the risk of getting spurious estimation results. Several methods have been derived to test for panel cointegration (see, e.g., Wagner and Hlouskova 2007, for a recent survey and performance test of alternative approaches). These can be classified as single-equation and system tests, with the most prominent operationalizations in time-series analysis being the Engle–Granger (1987) and Johansen (1991) VECM approaches, respectively. For this analysis, we apply the Kao (1999) and Pedroni (1999) panel ρ tests as residual based approaches in the spirit of the Engle–Granger and additionally a Fisher (1932) type test, where the latter combines the probability values for single cross-section estimates of the Johansen (1991) system approach.[5] If we get evidence for a stable cointegration relationship among the variables, we are then able to move on and specify different regression models which are capable of estimating non-stationary panel data models including information in levels and first differences.

Since we have rather limited time-series observations, this makes it hard to estimate individual models for each German region. A natural starting point would thus be to pool the time-series and cross-section data for purposes of estimation. However, this is only feasible if the data is actually 'poolable' (see, e.g., Baltagi 2008). Among the common estimation alternatives in this setting with small N and increasing T are the pooled mean group (PMG) and the dynamic fixed effects (DFE) model. While the PMG estimator allows for cross-section specific heterogeneity in the coefficients of the short run parameters of the model (see Pesaran et al. 1999), the DFE model assumes homogeneity of short and long-run parameters in the estimation approach. Given a consistent benchmark (such as the standard mean group estimator, see Pesaran and Smith 1995), we are also able to test for the appropriateness of the pooling approach by means of standard Hausman (1978) tests. Table 7.3 first presents the results of the cointegration tests among output, trade and FDI, Table 7.4 then gives a detailed overview of the regression output for the PMG and DFE estimator using the sample period 1976 to 2005.

If we first look at the panel cointegration tests in Table 7.3, we see that the Kao (1999) and Fisher-type Johansen (1991) tests clearly rejects the null hypothesis of no cointegration for the five variables employed. However, the result of the Pedroni panel ρ test is less clear cut. Here, we only get empirical support for a stable cointegration relationship at the 10% significance level. Regarding the estimated coefficients, the results in Table 7.4 show that we find a positive long-run effect of export activity on growth, both for the PMG and the DFE models. This is consistent

[5]The Fisher-type test can be defined as $-2\sum_{i=1}^{N}\log(\phi_i) \rightarrow \chi^2 2N$, where ϕ_i is the p-value from an individual Johansen cointegration test for cross-section i. Here, we apply the Fisher test to the maximum eigenvalue (χ-max) of the Johansen (1991) approach, which tests the null hypothesis of r cointegration relationships against the alternative of $(r+1)$ relationships. At this point we restrict the Johansen approach to test the null hypothesis of $rank \leq 0$. If the null hypothesis is rejected, for the underlying single cointegration vector we then assume that it has the form of a stylized output equation driven by trade and FDI as, e.g., outlined for the case of the augmented export base model outlined above.

Table 7.3 Panel cointegration tests for regional output, trade and FDI in the aspatial model

	Coint.	p-value
Kao (1999) ADF	-4.23^{***}	(0.00)
Pedroni (1999) ρ	2.01^{*}	(0.06)
χ-max of Johansen (1991)	115.2^{***}	(0.00)

Note: H_0 for panel cointegration tests is the no-cointegration case. For the Johansen maximum eigenvalue test MacKinnon–Haug–Michelis (1999) p-values are reported. The test is applied to the null hypothesis of rank ($r \leq 0$) against the alternative of ($r + 1$)

*Denote statistical significance at the 10% level **Denote statistical significance at the 5% level

***Denote statistical significance at the 1% level

Table 7.4 Aspatial model estimates for the growth–trade–FDI nexus

Dep. var.: Δy	PMG	DFE
Long run estimates		
ex_{it}	1.02^{***}	0.78^{***}
	(0.337)	(0.299)
im_{it}	-0.42^{*}	-0.47
	(0.224)	(0.323)
$fdi\ out_{it}$	-0.21	-0.15
	(0.157)	(0.235)
$fdi\ in_{it}$	0.16	0.16
	(0.118)	(0.169)
Short run estimates		
u_{it-1}	-0.06^{***}	-0.05^{***}
	(0.009)	(0.014)
Δy_{it-1}	0.29^{***}	0.33^{***}
	(0.048)	(0.048)
Δex_{it}	-0.08^{**}	-0.01
	(0.038)	(0.033)
Δim_{it}	0.10^{***}	0.07^{***}
	(0.016)	(0.022)
$\Delta fdi\ out_{it}$	0.07^{***}	0.06^{***}
	(0.019)	(0.013)
$\Delta fdi\ in_{it}$	0.06^{***}	0.06^{***}
	(0.012)	(0.013)
Hausman test $\chi^2(4)$	15.29^{***}	0.01
p-value	(0.00)	(0.00)
STMI residuals	5.96^{***}	7.45^{***}
p-value	(0.00)	(0.00)
p^b-value	(0.00)	(0.00)

Note: Standard errors in brackets. The Hausman test checks for the validity of the PMG and DFE specifications against the MG estimation results. *STMI* is the spatio-temporal extension of the Moran's I statistic, which tests for H_0 of spatial independence among observations. Since we are dealing with a small number of cross-sections, we use standard as well as bootstrapped p-values of the test. The latter are marked by a "b"

*Denote statistical significance at the 10% level

**Denote statistical significance at the 5% level

***Denote statistical significance at the 1% level

with the export-led growth theory of regional economics. However, for imports, we find a negative impact on GDP, which is, however, only statistically significant at the 10% level. The models do not find any long-run causation from FDI activity (both inward and outward) to GDP. Looking at the short-run coefficients, we see that the coefficient of the error correction term is statistically significant and of expected sign, although the speed of adjustment to the long-run equilibrium is rather slow (around 5–6% per year). Though we do not find a statistical long-run impact of import and FDI activity on economic growth, there is a multidimensional positive short-run correlation from import and both FDI variables to output growth. The sole exception is export flows, for which we do not find any short-run effect in the DFE model and a reversed coefficient sign in the PMG model.

If we finally check for the statistical appropriateness of the respective estimators, we see from the results of the Hausman m-statistic that only for the DFE model we cannot reject the null hypothesis of consistency and efficiency of the DFE relative to the benchmark mean group (MG) estimator.[6] On the contrary, the PMG is found to be inconsistent. Thus, we conclude that the DFE is the preferred (aspatial) model specification in the context of the German growth–trade–FDI nexus.

So far we did not account for the spatial dimension of the data. As Beenstock and Felsenstein (2010) point out, this may lead to a severe bias of the estimation results both in terms of the cointegration space of the variables as well as incomplete handling of spatial dependence in the model. To check for the appropriateness of our aspatial cointegration relationship from Table 7.4, we calculate a spatio-temporal extension to the Moran's I statistic (thereafter labeled *STMI*) for the estimated models' residuals, which has recently been proposed by Lopez et al. (2009). Since we are dealing with a small number of cross-sections, we compute both asymptotic as well as bootstrapped test statistics to get an indication of the degree of misspecification in the model. Lin et al. (2009) have shown that bootstrap based Moran's I values are an effective alternative to the asymptotic test in small-sample settings. Details about the computation of the *STMI* and bootstrapped inference are given in Appendix A. As the results show, the *STMI* strongly rejects the null hypothesis of spatial independence among the observed regions for both the asymptotic as well bootstrapped-based test statistic using a distance matrix based on common borders among German states. In sum, these results may be seen as a first strong indication that the absence of explicit spatial terms in the regression may induce the problem of spurious regression.

7.5.2 Global Cointegration and SpECM

We now move on to an explicit account of the spatial dimension both in the long- and short-run specification of the model. First, we estimate the long-run equation for

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[6] We do not report regression results of the MG estimator here. They can be obtained from the author upon request. The MG estimator assumes individual regression coefficients in the short- and long-run and simply averages the coefficients over the individuals. Pesaran and Smith (1995) have shown that this results in a consistent benchmark estimator.

Table 7.5 Panel cointegration tests for regional output, trade and FDI in the spatially augmented model

	Coint.	p-value
Kao (1999) ADF	-3.70^{***}	(0.00)
Pedroni (1999) ρ	2.74^{***}	(0.00)
χ-max of Johansen (1991)	741.0^{***}	(0.00)

Note: H_0 for panel cointegration tests is the no-cointegration case. For the Johansen maximum eigenvalue test MacKinnon–Haug–Michelis (1999) p-values are reported. The test is applied to the null hypothesis of rank ($r \leq 0$) against the alternative of ($r + 1$)

*Denote statistical significance at the 10% level **Denote statistical significance at the 5% level

***Denote statistical significance at the 1% level

Table 7.6 Spatially augmented long-run estimates of GDP, trade and FDI

Dep. var.: y	Spatial FEM	SDM-ML	SDEM-ML	SDM-GMM
ex_{it}	0.27^{***}	0.49^{***}	0.41^{***}	0.55^{**}
	(0.098)	(0.089)	(0.076)	(0.232)
im_{it}	0.08	−0.03	0.06	0.40
	(0.086)	(0.106)	(0.072)	(0.247)
$fdi\ out_{it}$	0.28^{***}	0.28^{***}	0.19^{***}	0.36^{**}
	(0.040)	(0.057)	(0.029)	(0.158)
$fdi\ in_{it}$	0.04	−0.01	0.06^{**}	−0.41
	(0.037)	(0.049)	(0.028)	(0.258)
ex^*_{it}	0.19^{*}	0.07	0.05	−0.02
	(0.101)	(0.049)	(0.078)	(0.320)
im^*_{it}	-0.20^{**}	-0.10^{**}	0.03	0.33
	(0.103)	(0.042)	(0.082)	(0.285)
$fdi\ out^*_{it}$	0.04	0.18^{***}	0.04	−0.04
	(0.049)	(0.032)	(0.036)	(0.084)
$fdi\ in^*_{it}$	−0.01	-0.05^{*}	−0.02	−0.01
	(0.048)	(0.029)	(0.034)	(0.147)
y^*_{it}		-0.23^{***}		−0.06
		(0.021)		(0.582)
$error^*$			0.19^{***}	
			(0.012)	

Note: Standard errors in brackets. The *SDM-GMM* uses up to two lags for the exogenous variables and their spatial lags, as well as the twice lagged value of the spatial lag of the endogenous variable

*Denote statistical significance at the 10% level

**Denote statistical significance at the 5% level

***Denote statistical significance at the 1% level

the relationship of GDP, trade, and FDI. The results for the augmented panel cointegration tests and different estimation strategies are shown in Tables 7.5 and 7.6, respectively. We start from a simple fixed effects specification. However, due to the inclusion of spatial lags, OLS estimation may lead to inconsistent estimates of the regression parameters (see, e.g., Fischer et al. 2009). Since (7.2) takes the form of a general spatial Durbin model, it may be appropriately estimated by maximum likelihood (ML), which has recently been proposed for panel data settings in Beer and Riedl (2009). The estimator of Beer and Riedl (2009) makes use of a fixed-effects (generalized Helmert) transformation proposed by Lee and Yu (2010) and maximizes the log-likelihood function with imposed functional form for the individual variances to keep the number of parameters to be estimated small (for details, see Beer and Riedl 2009). The authors show by means of a Monte Carlo simulation experiment that the SDM-ML estimator has satisfactory small-sample properties. Besides the SDM-ML model, which includes spatial lags of the endogenous and exogenous variables, we also estimate a spatial Durbin error model (SDEM), which includes spatial lags of the exogenous variables and a spatially lagged error term as well as estimate the SDM by GMM.

Again, we first look at the obtained test results from the panel cointegration tests including spatial lags of the exogenous variables. The results in Table 7.5 give strong empirical evidence that the variables cointegrated. Compared to the aspatial specification the result of the Pedroni (1999) test is improved (statistically significant at the 1% level), indicating that the inclusion of spatial lags of exogenous variables is necessary to ensure a stable cointegration relationship for a regional economic model as already pointed out by Felsenstein and Beenstock (2010).

Regarding the estimated coefficients, again we observe a positive effect from exports on GPD in the spatially augmented long-run relationship. The estimated elasticity is somewhat smaller compared to the aspatial estimators from above. Next to the direct export effect for the DFE, we also observe an indirect effect from the spatial lag of the export variable (ex^*). That is, an increased export activity in neighboring regions also spills over and leads to an increased GDP level in the home region. The effect, however, becomes insignificant if we move from a simple FEM regression to a ML based estimator for the general spatial Durbin model (SDM) and spatial Durbin error model (SDEM) as well as the GMM approach in Table 7.6.[7] All specifications show a significant direct effect of outward FDI on regional output. The latter can be associated with the FDI-led growth hypothesis. Additionally, the SDM-ML model also finds a significant positive coefficient for interregional spillovers from outward FDI stocks on the output level. The direct impact of import flows turns out to be insignificant. However, we get a significant negative coefficient for the indirect spillover effect (both for the FEM and SDM-ML), indicating that higher importing activity in neighboring regions are correlated with GDP levels in the own region. For inward FDI, we hardly find any direct or indirect spatial effect on GDP.

While the partial derivatives of direct and indirect effects for each exogenous variable can be immediately assessed for the FEM and SDEM-ML results in Table 7.6,[8] LeSage and Pace (2009) have recently shown that for model specifications including a spatial lag of the endogenous variable, impact interpretation is

[7] We specify the GMM approach in extension to the ML estimators, since the model may be a good candidate for estimation of the time and spatial dynamic processes in the second step short-run specification.

[8] This also holds for the SDM-GMM since the spatial lag coefficient of the dependent variable is insignificant.

Table 7.7 Direct, indirect and total effect of variables in SDM-ML

	Direct	Indirect	Total
ex_{it}	0.52^{***}	-0.07	0.46^{***}
im_{it}	0.03	-0.14	-0.11
$fdi\ out_{it}$	0.21^{***}	0.17^{***}	0.37^{***}
$fdi\ in_{it}$	0.03	-0.08	-0.05

Note: Using simulated parameters as described in LeSage and Pace (2009)
*Denote statistical significance at the 10% level **Denote statistical significance at the 5% level
***Denote statistical significance at the 1% level

more complex. Table 7.7 therefore additionally computes summary measures for the SDM-ML based on a decomposition of the average total effect from an observation into the direct and indirect effect. The table shows that there is a significant total effect of export flows on the regional GDP level, which can be almost entirely attributed to its direct effect. Imports and inward FDI are not found to have either a significant direct or indirect effect, while for the case of outward FDI, we find both a positive direct as well as indirect effect. The latter results contrast findings from the SDEM-ML, indicating a significant effect running from inward FDI to growth. As LeSage and Pace (2009) point out, we cannot directly judge about the validity of one of the two models, since the SDEM does not nest the SDM and vice versa. However, one potential disadvantage of the SDEM compared to the SDM is that it could result in severe underestimation of higher-order (global) indirect impacts (see LeSage and Pace 2009, for details). We may thus argue that SDM-ML is the most reliable specification for the long-run estimation of the output–trade–FDI system.

We then move on and use the obtained long-run cointegration relationship in a SpECM framework for regional GDP growth. The estimation results of the SpECM are shown in Table 7.8. For estimation of the SpECM, we apply the standard DFE model, the SDM-ML from Beer and Riedl (2009), as well as the spatial dynamic GMM specification. The latter estimator explicitly accounts for the endogeneity of the time lag of the dependent variable by valid instrumental variables. Although the time dimension of our data is reasonably long, the bias of the fixed effects estimator may still be in order.[9] The spatial dynamic GMM estimator using an augmented instrument set in addition to the aspatial version proposed by Arellano and Bond (1991) as well as Blundell and Bond (1998) has recently performed well in Monte Carlo simulations (see Kukenova and Monteiro 2009) as well as in empirical applications (e.g., Bouayad-Agha and Vedrine 2010). Valid moment conditions for instrumenting the spatial lag of the endogenous variable besides the time lag are given in Appendix B. The inclusion of time and spatial lags in the SpECM results in a 'time–space-simultaneous' specification (see, e.g., Anselin et al. 2007).

With respect to the included variables, all model specifications report qualitatively similar results. For the standard EC-term we get a highly significant regression

[9] Using Monte Carlo simulations, Judson and Owen (1999), for instance, report a bias of about 20% of the true parameter value for the FEM, even when the time dimension is $T = 30$.

Table 7.8 Spatially augmented short-run estimates of GDP, trade and FDI

Dep. var.: Δy	DFE	SDM-ML	SDM-GMM
u_{it-1}	-0.16^{***}	-0.05^{*}	-0.21^{***}
	(0.025)	(0.033)	(0.034)
u^{*}_{it-1}	0.14^{***}	-0.01	0.20^{***}
	(0.025)	(0.012)	(0.036)
Δy_{it-1}	0.49^{***}	0.36^{***}	0.47^{***}
	(0.040)	(0.099)	(0.049)
Δex_{it}	0.04	0.06	0.03
	(0.032)	(0.051)	(0.044)
Δim_{it}	0.10^{***}	0.06	0.14^{***}
	(0.024)	(0.047)	(0.011)
$\Delta fdi\ out_{it}$	0.09^{***}	0.07^{***}	0.08^{***}
	(0.016)	(0.025)	(0.019)
$\Delta fdi\ in_{it}$	0.06^{***}	0.06^{***}	0.06^{***}
	(0.012)	(0.020)	(0.011)
Δex^{*}_{it}	0.05^{**}	0.01	0.02^{*}
	(0.021)	(0.026)	(0.010)
Δim^{*}_{it}	-0.04^{*}	-0.01	-0.04^{**}
	(0.019)	(0.183)	(0.013)
$\Delta fdi\ out^{*}_{it}$	0.01	0.02	-0.02
	(0.009)	(0.014)	(0.018)
$\Delta fdi\ in^{*}_{it}$	0.01	0.06^{***}	0.01
	(0.011)	(0.011)	(0.010)
Δy^{*}		0.22^{***}	0.11^{**}
		(0.036)	(0.044)
STMI residuals	-2.85^{***}	-1.08	-1.41
p-value	(0.00)	(0.14)	(0.08)
p^{b}-value	(0.00)	(0.84)	(0.12)

Note: Standard errors in brackets

*Denote statistical significance at the 10% level

**Denote statistical significance at the 5% level

***Denote statistical significance at the 1% level

parameter in the DFE- and GMM-based specification, which is of expected sign. Besides the results from the panel cointegration tests from Table 7.6, this is a further indication that GDP and the variables for internationalization activity co-move over time in a long-run cointegration relationship, where short-term deviations balance out in the long-run. For the size of the EC-term, the spatial dynamic GMM model comes closest to values typically found in the empirical literature, with about one-fifth of short-run deviations being corrected after one year (see, e.g., Ekanayake et al. 2003). Also, the coefficient for the spatialized EC-term (u^{*}) is significantly different from zero in the DFE and GMM specification.

Looking at the short-run correlation between growth, trade, and FDI in Table 7.8, we see that both direct and indirect (spatial) forces are present. As for the direct effects, the results do not differ substantially from the aspatial SpECM specification in Table 7.4. We do not find any significant short-run effect from export activity on growth. However, all other variables are positively correlated with the latter. Looking more carefully at the spatial counterparts of these variables, we see that a higher export activity has a positive spillover effect on the output growth of neighboring regions while imports have a negative indirect effect (in line with the long-run findings). We also check for the significance of spatial lags in the endogenous variable and the error term. Here we find that there are indeed spatial spillovers from an increased growth performance in neighboring regions, a result which mirrors related findings for German regional growth analysis (see, e.g., Niebuhr 2000, as well as Eckey et al. 2007). This result is also supported by the significant and positive coefficient for the spatial lag of the error correction variable (u^*). We do not find any sign for significant spatial autocorrelation left in the residuals of the SDM-ML and SDM-GMM using the (bootstrapped) *STMI* test.

7.6 Robustness Check: Transport Flows as Spatial Weights

The use of an appropriate spatial weighting matrix is a delicate issue in spatial econometrics (Elhorst 2010). In order to check the stability of the short- and long-run results, we thus use an alternative weighting matrix, which employs interregional economic linkages based on transport flows for goods rather than geographical information. Since a total measure of interregional trade flows among German regions is not available, railway transportation statistics may serve as a proxy for the former. We use data from 1970 to ensure that the observed interregional linkages are exogenous to our estimation system (see Table 7.9). A further motivation for using the transport-based weighting scheme is that we are able give a more straightforward

Table 7.9 Interregional railway transportation flows in 1970 (in 1000 tons)

From:/To:	SH	HH	NIE	BRE	NRW	HES	RHP	BW	BAY	SAAR	Total
SH	966	176	679	94	340	102	63	206	289	9	2924
HH	321	896	2297	374	933	342	118	361	747	27	6416
NIE	1303	1033	20434	1593	7288	1465	391	890	2140	3726	40263
BRE	42	61	3182	3158	1449	386	193	420	600	111	9602
NRW	2064	2191	11056	4705	102530	5114	3271	4821	7737	2064	145553
HES	195	491	958	517	1823	4512	782	942	1583	158	11961
RHP	181	177	618	231	2013	895	2337	2916	1722	1097	12187
BW	68	308	305	254	961	852	696	10853	2711	517	17525
BAY	143	468	578	364	1644	813	451	2225	19349	145	26180
SAAR	21	108	181	276	659	407	774	1471	898	7761	12556
Total	5304	5909	40288	11566	119640	14888	9076	25105	37776	15615	285167

Source: Statistisches Bundesamt, Fachserie H, R 4, Eisenbahnverkehr, 1970

Table 7.10 Spatially augmented short-run estimates

Dep. var.: Δy	DFE	SDM-ML	SDM-GMM
u_{it-1}	-0.13^{***}	-0.12^{***}	-0.21^{***}
	(0.023)	(0.022)	(0.033)
u^*_{it-1}	0.12^{***}	0.11^{***}	0.20^{***}
	(0.026)	(0.024)	(0.039)
Δy_{it-1}	0.52^{***}	0.48^{***}	0.46^{***}
	(0.041)	(0.041)	(0.052)
Δex_{it}	0.06^{*}	0.05	0.03
	(0.033)	(0.031)	(0.048)
Δim_{it}	0.08^{***}	0.09^{***}	0.14^{***}
	(0.025)	(0.023)	(0.016)
$\Delta fdi\ out_{it}$	0.08^{***}	0.08^{***}	0.08^{***}
	(0.016)	(0.015)	(0.017)
$\Delta fdi\ in_{it}$	0.06^{***}	0.06^{***}	0.06^{***}
	(0.013)	(0.012)	(0.007)
Δex^*_{it}	0.01	0.01	-0.08^{*}
	(0.035)	(0.033)	(0.037)
Δim^*_{it}	-0.07^{*}	-0.07^{**}	-0.02
	(0.042)	(0.039)	(0.040)
$\Delta fdi\ out^*_{it}$	0.02	0.02	-0.06^{*}
	(0.023)	(0.021)	(0.028)
$\Delta fdi\ in^*_{it}$	0.03	0.01	0.01
	(0.023)	(0.012)	(0.030)
Δy^*		0.19^{***}	0.25^{***}
		(0.061)	(0.066)
STMI residuals	-2.325^{***}	-0.377	-0.494
p-value	(0.01)	(0.35)	(0.31)
p^b-value	(0.00)	(0.80)	(0.06)

Note: Standard errors in brackets

*Denote statistical significance at the 10% level

**Denote statistical significance at the 5% level

***Denote statistical significance at the 1% level

economic interpretation regarding the estimation results. That is, for instance, consider a negative correlation of the neighboring regions' import performance with regional GDP evolution. Opening up for international trade in terms of increased import activity may lead to a substitution effect of interregional forward and backward linkages in Germany. Thus, regional supply from the region is substituted by its neighbors through international import flows. This, in turn, may slow down economic development in the region under study and can motivate a negative spatial spillover effect from import activity in neighboring regions of Germany.

Table 7.10 reports the result for the SpECM estimation for the DFE with spatial lags of the exogenous variables, the ML- and GMM-based spatial Durbin model. The results show that the parameters are rather stable with respect to the chosen estimator and the alternative specification of the spatial weighting matrix.[10] The error correction mechanism and its spatial lag are almost of equal magnitude compared to the border-based weighting scheme. Likewise, both the time and the spatial lag of regional GDP growth are important factors driving the dynamics of the model. Again, we find positive direct correlations between imports, inward FDI, outward FDI and GDP growth. Regarding the correlation of the indirect spatial coefficients, import flows exhibit a negative indirect effect, which turns out to be significant in the DFE and ML specifications. We find negative indirect effects for export and outward FDI in the SYS-GMM model (at the 10% significance level). The inspection of the residuals using the *STMI* shows both for the ML and SYS-GMM based SDM specification on average no remaining spatial dependence in the residuals (with only weak significance at the 10% level for the bootstrap version in the SYS-GMM model). These results closely match findings for the common-border-based weighting scheme. In contrast, the DFE model still exhibits spatial autocorrelation in the residuals.

7.7 Conclusion

The aim of this chapter was to analyze the role of within and between panel cointegration for the German regional output–trade–FDI nexus. While investigating the co-movements among non-stationary variables is by now a common standard in panel time-series analysis, less attention has been paid to the importance of spatial lags in the long-run formulation of a regression model. Applying the novel concept of global cointegration, as recently proposed by Beenstock and Felsenstein (2010), enables us to estimate spatially-augmented error correction models (SpECM) for West German data between 1976 and 2005. Our results show that both direct as well as indirect spatial linkages among the variables matter when tracking their long-run co-movement.

First, the regression results for the long-run equation give empirical support for a direct cointegration relationship among economic output and internationalization activity. In particular, export flows show a significant and positive long-run impact on GPD, supporting the export-led growth hypothesis from regional and international economics. Moreover, we also get evidence that outward FDI drives output in the long-run. Second, besides these direct effects, the latter variable is also found to exhibit significant positive spatial spillovers. In general, augmenting the model by spatial lags of the trade and FDI variables significantly increases the model performance both regarding the applied panel cointegration tests as well as tests for spatial dependence in the regression residuals. Our results can thus be interpreted in similar veins as Beenstock and Felsenstein (2010), who find that the inclusion of spatial lags of exogenous variables may have important implications for the stability of a cointegration relationship among variables for a regional economic system. As

[10]This also holds for the long-run estimates, which can be obtained from the author upon request.

empirical identification strategy in the spatially augmented model we employ both ML- as well as GMM-based estimators.

Regarding the short-run determinants of economic growth, for most variables in the specified spatial error correction model (SpECM) we observe positive direct effects. Regarding the spatial lags, we find that a rise in the export flows in neighboring regions significantly increases the region's own growth rate, while imports show negative feedback effects. Finally, we also find positive growth relationship among German regions if we augment the model by the spatial lag of the endogenous variables. This result mirrors earlier evidence for Germany, reporting positive spatial autocorrelation in regional growth rates. Our specified SpECM (both using ML as well as GMM with appropriate instruments for the time and spatial lag of the endogenous variable) passes residual based spatial dependence tests. For the latter, we use a spatio-temporal extension of the Moran's I statistic, for which we calculate both asymptotic as well as bootstrapped standard errors. We finally also test the stability of the results by using a different spatial weighting matrix based on interregional goods transport flows rather than geographical information. Our results hold for both spatial weighting schemes, giving strong evidence for the existence of direct and indirect effects in the German regional output–trade–FDI relationship, both in the long-run as well as dynamic short-run perspective.

Appendix A: Bootstrapping the Spatio-Temporal Extension of Moran's *I*

For a general description of the spatio-temporal extension of Moran's I (*STMI*) see Appendix A of Chap. 4. Building upon recent findings by Lin et al. (2009) for the standard Moran's I test, here we develop a 'wild' bootstrap based test version for the *STMI*, which can be implemented through the following steps:

Step 1 Estimate the residuals $\hat{e}_{it}$ as $\hat{e}_{it} = y - V\hat{\delta}$ for the spatial or aspatial estimator with regressors V and coefficients $\hat{\delta}$ (either short- or long-run specification) in focus and obtain a value for the *STMI*. Save the obtained *STMI*.

Step 2 Re-scale and re-center the regression residuals $\tilde{e}_{it}$ according to

$$\tilde{e}_{it} = \frac{\hat{e}_{it}}{(1 - h_{it})^{1/2}}, \tag{7.5}$$

where h_{it} is the model's projection matrix so that a division by $(1 - h_{it})^{1/2}$ ensures that the transformed residuals have the same variance (for details, see MacKinnon 2002).

Step 3 Choose the number of bootstrap samples B and proceed as follows for any j sample with $j = 1, \ldots, B$:

- **Step 3.1** According to the wild bootstrap procedure, multiply $\tilde{e}_{it}$ with $\tilde{\upsilon}_{it}$, where the latter is defined as a two-point distribution (the so-called Rademacher distribution) with

$$\tilde{\upsilon}_{it} = \begin{cases} 1 & \text{with probability } 1/2, \\ -1 & \text{with probability } 1/2. \end{cases} \tag{7.6}$$

- **Step 3.2** For each of the $i = 1, \ldots, N$ cross-sections, draw randomly (with replacement) T observations with probability $1/T$ from $\tilde{e}_{it} \times \tilde{\upsilon}_{it}$ to obtain $\tilde{e}^*_{it}$.
- **Step 3.3** Generate a bootstrap sample for variable y (and its spatial lag) as

$$y^*_{it} = V^*\hat{\delta} + \tilde{e}^*_{it}, \tag{7.7}$$

  where $V^* = (Wy^*_{it}, y^*_{it-1}, X)$ and, for a time-dynamic specification, initialization as $y^*_{i0} = y_{i0}$. Thus, for a regression equation with a lagged endogenous variable, we condition on the initial values of y_{i0}, the exogenous variables X, and the spatial weighting matrix W.[11]
- **Step 3.4** Obtain the residuals from the regression including y^* and V^*, calculate the bootstrap based STMI^*.

The full set of resulting bootstrap test statistics are $\mathit{STMI}^*_1, \mathit{STMI}^*_2, \ldots, \mathit{STMI}^*_B$. From the empirical distribution, we can then calculate p-values out of the nonparametric bootstrap exercise in order to perform hypothesis testing. There are various ways to do so. Lin et al. (2009), for instance, express equal-tail p-values for STMI^* as

$$P^*(\mathit{STMI}^*) = 2\min\left(\frac{1}{B}\sum_{j=1}^{B} C(\mathit{STMI}^*_j \leq \mathit{STMI}), \frac{1}{B}\sum_{j=1}^{B} C(\mathit{STMI}^*_j > \mathit{STMI})\right), \tag{7.8}$$

where $C(.)$ denotes the indicator function, which is equal to 1 if its argument is true and zero otherwise. Then, given a nominal level of significance α, we compare $P^*(\mathit{STMI}^*_j)$ with α. Following Lin et al. (2009), one can reject the null hypothesis of no spatial dependence if $P^*(\mathit{STMI}^*_j) < \alpha$.

Appendix B: Moment Conditions for the Spatial Dynamic GMM Model

The use of GMM-based inference in dynamic panel data models is a common practice in applied research. Most specifications rest on instruments sets as proposed by Blundell and Bond (1998). Their so-called system GMM (SYS-GMM) approach

[11] See, e.g., Everaert and Pozzi (2007) for the treatment of initial values to bootstrap dynamic panel data processes. In the following, by default, we generate y^* based on the long-run cointegration specification, where we do not face the problem of time dynamics in the bootstrapping exercise. However, we additionally need to account for the generated error term and its spatial lag as explanatory regressors in the short-run equation.

combines moment conditions for the joint estimation of a regression equation in first differences and levels. The latter part helps to increase the efficiency of the GMM methods compared to earlier specifications solely in first differences (e.g., Arellano and Bond 1991). Subsequently, extensions of the SYS-GMM approach have been proposed, which make use of valid moment conditions for the instrumentation of the spatial lag coefficient of the endogenous variable (see, e.g., Kukenova and Monteiro 2009; Bouayad-Agha and Vedrine 2010). Kukenova and Monteiro (2009) have also shown, by means of Monte Carlo simulations, that the spatial dynamic SYS-GMM model exhibits satisfactory finite sample properties.

For the purpose of this analysis, we focus on appropriate moment conditions for the time–space simultaneous model including a time and spatial lag of the endogenous variable. Instruments can be built based on transformations of the endogenous variable as well as the set of exogenous regressors. Assuming strict exogeneity of current and lagged values for any exogenous variable $x_{i,t}$, then the full set of potential moment conditions for the spatial lag of $y_{i,t-1}$ is given by

- First differenced equation:

$$E\left(\sum_{i \neq j} w_{ij} \times y_{i,t-s} \quad \Delta u_{i,t}\right) = 0, \quad t = 3, \ldots, T, s = 2, \ldots, t-1, \tag{7.9}$$

$$E\left(\sum_{i \neq j} w_{ij} \times x_{i,t \pm s} \quad \Delta u_{i,t}\right) = 0, \quad t = 3, \ldots, T, \quad \forall s. \tag{7.10}$$

- Level equation:

$$E\left(\sum_{i \neq j} w_{ij} \times \Delta y_{i,t-1} \quad u_{i,t}\right) = 0, \quad t = 3, \ldots, T, \tag{7.11}$$

$$E\left(\sum_{i \neq j} w_{ij} \times \Delta x_{i,t} \quad u_{i,t}\right) = 0, \quad t = 2, \ldots, T. \tag{7.12}$$

One has to note that the consistency of the SYS-GMM estimator relies on the validity of these moment conditions. Moreover, in empirical application we have to carefully account for the ‘many’ and/or ‘weak instrument’ problem typically associated with GMM estimation, since the instrument count grows as the sample size T rises. We thus put special attention to this problem and use restriction rules specifying the maximum number of instruments employed as proposed by Bowsher (2002) and Roodman (2009).

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Part III
Growth, Factor and Final Demand

Chapter 8
Dynamic Simultaneous Equations with Panel Data: Small Sample Properties and Application to Regional Econometric Modelling

8.1 Introduction

The notion of simultaneity among variables arises for many economic relations. This chapter seeks to analyze the appropriateness of different dynamic panel data models for estimating small simultaneous equation systems. Using multiple equation extensions for the standard fixed effects model (FEM), a bias corrected FEM version as well as different IV and GMM estimators, recently proposed in the literature, we judge among their performance in terms of bias and efficiency in Monte Carlo simulations. Beside standard large N (cross-sections), small T (time dimension) assumptions we especially check for the estimators performance in two-sided small samples with both moderate N and T. The latter setup is typically found for data settings involving macroeconomic or regional analysis.

In an empirical application, we then estimate dynamic simultaneous equation modelling with panel data to assess the role of spillovers from public capital formation and regional support policies for the regional growth of German states (NUTS1-level). We explicitly set up a system of equations in order to account more appropriately for the possible sources of endogeneity for right-hand-side regressors in the output and factor demand equations. Compared to the single-equation approach, the system estimation is also able to spell out feed-back simultaneities among the endogenous variables specified in the system and identify the direct and indirect effects of policy variables on labor productivity growth and private/public capital investment.

The remainder of the chapter is organized as follows: Sect. 8.2 specifies the underlying econometric model involving a system of equations, where at least one equation is of dynamic nature by the inclusion of a lagged endogenous variable as right-hand-side regressor. Section 8.3 sketches the Monte Carlo simulation design and discusses the results for a set of different parameter constellations. For the empirical application in Sect. 8.4 we build up a small-scale 3-equation regional growth model for labor productivity with endogenized equations for private and public capital input. We check the dynamic properties of the system and use the model for regional policy analysis. The latter tests for the economic effects of interregional

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public capital spillovers and regional equalization transfer schemes. Section 8.5 concludes the chapter.

8.2 Model Setup: DSEM with Panel Data

8.2.1 General Specification

Consider a system of M dynamic equations, where its m-th structural equation has the following general form

$$y_{i,t,m} = \alpha + \sum_{j=0}^{l} \beta_j' Y_{i,t-j,m} + \sum_{j=0}^{k} \gamma_j' X_{i,t-j,m} + u_{i,t,m}, \quad \text{with } u_{i,t,m} = \mu_{i,m} + \nu_{i,t,m}, \tag{8.1}$$

for $i = 1, \ldots, N$ (cross-sectional dimension) and $t = 1, \ldots, T$ (time dimension). $y_{i,t,m}$ is the endogenous variable and $Y_{i,t,m}, \ldots, Y_{i,t-j,m}$ denote current and lagged endogenous explanatory variables of the system including the lagged endogenous variable of the m-th equation. Analogously, X is a $(1 \times K)$ vector of all further (unmodelled) K explanatory regressors, $u_{i,t,m}$ is the combined error term, which is composed of the two error components $\mu_{i,m}$ as the unobservable individual effects and $\nu_{i,m}$ is the remainder error term. Both $\mu_{i,m}$ and $\nu_{i,t,m}$ are assumed to be i.i.d. residuals with standard normality assumptions as

$$\begin{aligned} E(\nu_{i,t,m}\nu_{j,s,m}) &= 0, \quad \text{for either } i \neq j \text{ or } t \neq s, \text{ or both,} \\ E(\mu_{i,m}\mu_{j,m}) &= 0, \quad \text{for } i \neq j, \\ E(\mu_{i,m}\nu_{j,t,m}) &= 0, \quad \forall i, j, t, \end{aligned} \tag{8.2}$$

where j and s have the same dimension as i and t, respectively. The first two assumptions state that the homoscedastic error terms are mutually uncorrelated over time and across cross-sections. Furthermore the unobserved individual heterogeneity is random and uncorrelated between individuals. The third assumption rules out any correlation between the individual effects and the remainder of the disturbance term. One has to note, that these assumptions hold for the error components of the m-th equation of the system, while we allow for cross error correlations between different equations of the system. Stacking the observations for each endogenous $y_{i,t}$, exogenous variable $x_{i,t}$ and the error term $u_{i,t}$ according to

$$y = \begin{pmatrix} y_{11} \\ \vdots \\ y_{iT} \\ \vdots \\ y_{NT} \end{pmatrix}, \quad x = \begin{pmatrix} x_{11} \\ \vdots \\ x_{iT} \\ \vdots \\ x_{NT} \end{pmatrix}, \quad u = \begin{pmatrix} u_{11} \\ \vdots \\ u_{iT} \\ \vdots \\ u_{NT} \end{pmatrix} \tag{8.3}$$

allows us to simplify the notation of (8.1) in the following way:

$$y_m = R_m \xi_m + u_m, \quad u_m = \mu_m + \nu_m, \tag{8.4}$$

where $R_n = (Y_n, X_n)$ and $\xi = (\beta', \gamma')$. Further stacking the equations into the form usual considered in a system analysis yields

$$y = R\xi + u, \tag{8.5}$$

where $y' = (y_1', \ldots, y_M')$ and similar for ξ and u. R is defined as

$$R = \begin{bmatrix} R_1 & \cdots & 0 \\ \vdots & \ddots & \vdots \\ 0 & \cdots & R_M \end{bmatrix}. \tag{8.6}$$

As in the single equation model, we assume that both μ and ν are standard normal errors with the zero mean and covariance matrices for the error components as $\Sigma_\mu = [\sigma^2_{\mu_{(j,l)}}]$ (with $j = 1, \ldots, M$ and $l = 1, \ldots, M$) for the unobserved individual effects, and $\Sigma_\nu = [\sigma^2_{\nu_{(j,l)}}]$ for the remainder error term, respectively.

As Krishnakumar (1995) points out, directly estimating the coefficients of a structural equation of a simultaneous equation model by OLS or generalized least squares (GLS) leads to inconsistent estimators, since the explanatory endogenous variables of the equation are correlated with the error terms. In such cases, the method of instrumental variables (IV) is an appropriate technique of estimation. Typically, all contemporaneous and lagged values of the exogenous explanatory variables (X) are used as instruments for the set of endogenous variables. In the case of dynamic panel data estimators, the instrumentation problem is even more complex, since appropriate instruments for the lagged regressors of the endogenous variable have to be found as well.

8.2.2 *Estimators for Dynamic Panel Data Models*

In the recent literature, various contributions have been proposed on how to deal with the problem introduced by the inclusion of a lagged dependent variable in the estimation of a dynamic panel data model and its built-in correlation with the individual effect: That is, since y_{it} is a function of μ_i, also $y_{i,t-1}$ is a function of μ_i and thus $y_{i,t-1}$ as right-hand side regressor is correlated with the error term. Even in the absence of serial correlation of ν_{it}, this renders standard λ-class estimators such as OLS, FEM and random effects (REM) models biased and inconsistent (see, e.g., Nickell 1981; Sevestre and Trognon 1995 or Baltagi 2008, for an overview). Since the single equation dynamic panel data model is a nested version of (8.1), which basically reduces the vector Y to $y_{i,t-1,m}$, we first discuss solutions for the instrumentation problem along the lines of the single equation literature. The extension to the system case is then rather straightforward. The most widely applied approaches of dealing with this kind of endogeneity typically start with first differencing (FD) (8.1) to get rid of μ_i and then estimate the model by IV techniques. The advantage of the FD transformation is that this form of data transformation does not invoke the inconsistency problem associated with the standard FEM or REM estimation (see, e.g., Baltagi 2008). Anderson and Hsiao (1981) were among the first to propose an estimator for the transformed FD model of the nested single equation version (8.1):

$$(y_{it} - y_{i,t-1}) = \alpha(y_{i,t-1} - y_{i,t-2}) + \sum_{j=1}^{k} \beta_j (X_{i,t-j} - X_{i,t-j+1}) + (u_{it} - u_{i,t-1}), \tag{8.7}$$

where $(u_{it} - u_{i,t-1}) = (\nu_{it} - \nu_{i,t-1})$ since $(\mu_i - \mu_i) = 0$. As a result of first differencing, the unobservable individual effects have been eliminated from the model. However, the error term $(\nu_{it} - \nu_{i,t-1})$ is correlated with $(y_{i,t-1} - y_{i,t-2})$ and thus the latter needs to be estimated by appropriate instruments which are uncorrelated with the error term. Anderson and Hsiao (1981) recommend to use lagged variables, either the lagged observation $y_{i,t-2}$ or the lagged difference $(y_{i,t-2} - y_{i,t-3})$ as instruments for $(y_{i,t-1} - y_{i,t-2})$. Arellano (1989) compares the two alternatives and recommends $y_{i,t-2}$ rather than the lagged differences as instruments since they typically show a superior empirical performance in terms of bias and efficiency. The respective orthogonality conditions for this IV approach can be stated as:

$$E(y_{i,t-2}\,\Delta u_{i,t}) = 0 \quad \text{or alternatively} \quad E(\Delta y_{i,t-2}\,\Delta u_{i,t}) = 0, \tag{8.8}$$

where Δ is the difference operator defined as $\Delta u_{i,t} = u_{i,t} - u_{i,t-1}$ and likewise for y. The Anderson–Hsiao (AH) model can only be estimated for $t = 3, \ldots, T$ due to the construction of the instruments. Subsequently, refined instrument sets for the estimation of (8.7) have been proposed in the literature. Trying to improve the small sample behavior of the AH estimator, Sevestre and Trognon (1995) propose a more efficient FD estimator which is based on a GLS transformation of (8.7).[1] Searching for additional orthogonality conditions, Arellano and Bond (1991) propose an GMM estimator, which makes use of all lagged endogenous variables—rather than just $y_{i,t-2}$ or $\Delta y_{i,t-2}$—of the form:[2]

$$E(y_{i,t-\rho}\,\Delta u_{i,t}) = 0 \quad \text{for all } \rho = 2, \ldots, t-1 \text{ and } t = 3, \ldots, T. \tag{8.9}$$

Equation (8.9) is also called the 'standard moment condition' and is widely used in empirical estimation. Thus, for each individual i, the full set of valid instruments (including also a strictly exogenous regressor $x_{i,t}$) may be written compactly as

$$E(\mathbf{Z}_i'^{DIF}\,\Delta u_i) = 0 \tag{8.10}$$

[1] Since this GLS transformation leads to disturbances that are linear combinations of the $u_{i,t}$'s, the only valid instruments for $\Delta y_{i,t-1}$ are current and lagged values of ΔX.

[2] The use of GMM in dynamic panel data models was introduced by Holtz-Eakin et al. (1988), who propose a way to use 'uncollapsed' IV sets.

where the matrix $\mathbf{Z}_i'^{DIF}$ has the following form

$$\mathbf{Z}_i'^{DIF} = \begin{pmatrix} y_{i1} & 0 & 0 & 0 & 0 & 0 & \cdots & 0 & \cdots & 0 & \Delta x_{i3} \\ 0 & y_{i1} & y_{i2} & 0 & 0 & 0 & \cdots & 0 & \cdots & 0 & \Delta x_{i4} \\ 0 & 0 & 0 & y_{i1} & y_{i2} & y_{i3} & \cdots & 0 & \cdots & 0 & \Delta x_{i5} \\ \vdots & \vdots & \vdots & \vdots & \vdots & \vdots & \ddots & \vdots & \ddots & \vdots & \vdots \\ 0 & 0 & 0 & 0 & 0 & 0 & \cdots & y_{i1} & \cdots & y_{i,(T-2)} & \Delta x_{i,T} \end{pmatrix}. \tag{8.11}$$

However, one general drawback of the Arellano–Bond type dynamic GMM estimator in first differences is a rather poor empirical performance especially when the persistence in the coefficient for the lagged endogenous variable is high or the variance of the individual effects μ_i large relative to the total variance in $u_{i,t}$ (see e.g. Soto 2009, for a discussion; Munnell 1992, and Holtz-Eakin 1994, provide empirical evidence for the estimation of a production function using AB-GMM, Bond et al. (2001) get similar results for growth equation estimates). Bond et al. (2001) argue that the first difference estimators may behave poorly, since lagged levels of the time series provide only 'weak instruments' for sub-sequent first-differences.

In response to this critique, a second generation of dynamic panel data models has been developed which also makes use of appropriate orthogonality conditions (in linear form) for the equation in levels (see e.g. Arellano and Bover 1995; Ahn and Schmidt 1995, and Blundell and Bond 1998) as[3]

$$E(\Delta y_{i,t-1} u_{i,t}) = 0 \quad \text{for } t = 3, \dots, T. \tag{8.12}$$

Thus, rather than using lagged levels of variables for equations in first difference as in the FD estimators, we now get an orthogonality condition for the model in level that uses instruments in first differences. Equation (8.12) is also called the 'stationarity moment condition'.[4] Written compactly as

$$E(\mathbf{Z}_i'^{LEV}\ \Delta u_i) = 0 \tag{8.13}$$

the matrix $\mathbf{Z}_i'^{LEV}$ is given by

$$\mathbf{Z}_i'^{LEV} = \begin{pmatrix} \Delta y_{i2} & 0 & \cdots & 0 & x_{i3} \\ 0 & \Delta y_{i3} & \cdots & 0 & x_{i4} \\ \vdots & \vdots & \ddots & \vdots & \vdots \\ 0 & 0 & 0 & \Delta y_{i,(T-1)} & x_{i,T} \end{pmatrix}, \tag{8.14}$$

for the case that $x_{i,t}$ is strictly exogenous. Blundell and Bond (1998) propose a GMM estimator that jointly uses both the standard and stationarity moment condi-

[3]The original form in Ahn and Schmidt (1995) is $E(\Delta y_{i,t-1} u_{i,T}) = 0$ for $t = 3, \dots, T$ derived from a set of non-linear moment conditions. Blundell and Bond (1998) rewrote it as in (8.12) for convenience. The latter moment condition is also proposed in Arellano and Bover (1995).

[4]That is because for (8.12) to be valid we need an additional stationarity assumption concerning the initial values $y_{i,1}$. Typically $y_{i,1} = \mu/(1-\alpha) + w_{i,1}$ is considered as an initial condition for making $y_{i,t}$ mean-stationary, with assumptions on the disturbance $w_{i,1}$ as $E(\mu_i w_{i,1}) = 0$ and $E(w_{i,1} v_{i,t}) = 0$.

tions. This latter approach is typically labeled 'system' GMM as a combination of 'level' and 'difference' IV/GMM. Note however that this estimator still treats the data system as a single-equation problem since the same linear functional relationship is applied both for the FD-transformed and untransformed variables (see e.g. Roodman 2009). The resulting instrument set of the Blundell–Bond (BB-)GMM estimator is given by

$$\mathbf{Z}_i^{BB} = \begin{pmatrix} \mathbf{Z}_i^{DIF} & 0 \\ 0 & \mathbf{Z}_i^{LEV} \end{pmatrix}. \tag{8.15}$$

Building upon the instrument set $\mathbf{Z}_i^{BB}$ the extension of the single equation GMM approach—in first differences, levels as well as combined—is rather simple. As Hayashi (2000) points out, this is because the multiple-equation GMM estimator can be expressed as a single-equation estimator by suitably specifying the matrices and vectors comprising the latter approach. The advantage from the multiple equation approach is that joint estimation may improve efficiency. However, joint estimation may also be sensitive to misspecifications of individual equations. To work out the pros and cons more clearly, in the following, we set up the above described GMM-estimators for dynamic panel data in a multiple equation setting.

8.2.3 *Extension of GMM Estimation for Multiple Equation Settings*

Starting with the IV set from (8.15) for BB-GMM as an example, the joint orthogonality conditions for the M-equation system are just a collection of the orthogonality conditions for individual equations as $Z_i^{BB,S} = [Z_{i,1}^{BB}, Z_{i,2}^{BB}, \ldots, Z_{i,M}^{BB}]'$, where the subscript S denotes the system case. For the most general case, we do not assume cross orthogonalities, that is, for instance, the instrument set for equation 1 does not need to be orthogonal to the error term in equation 2 and so on. Only if a variable is included both in the instrument set for equations 1 and 2, it also has to be orthogonal to the error terms in equations 1 and 2, respectively. The main difference between the single and multiple equation GMM estimators rests on the specification of the weighting matrix for (two-step efficient) GMM estimation. This can be seen from the definition of the multiple equation GMM (henceforth SGMM) estimators for the M-equation system as (see e.g. Hayashi 2000, for details):

$$\hat{\Phi}_{SGMM} = \left(S'_{ZX}(V^S)^{-1}S_{ZX}\right)^{-1} S'_{ZX}(V^S)^{-1}S_{Zy}, \tag{8.16}$$

$$\text{with} \quad S_{ZX} = \begin{bmatrix} \frac{1}{N}\sum_{i=1}^{N} Z'_{i1}x_{i1} & & \\ & \ddots & \\ & & \frac{1}{N}\sum_{i=1}^{N} Z'_{iM}x_{iM} \end{bmatrix} \quad \text{and} \tag{8.17}$$

$$S_{Zy} = \begin{bmatrix} \frac{1}{N}\sum_{i=1}^{N} Z'_{i1}y_{i1} \\ \vdots \\ \frac{1}{N}\sum_{i=1}^{N} Z'_{iM}y_{im} \end{bmatrix}. \tag{8.18}$$

The above equations are basically the SGMM operationalization of the stylized system presentation given in (8.5) and (8.6). In empirical terms, the two-step efficient weighting matrix V^S has the following form

$$\hat{V}^S = \begin{bmatrix} \frac{1}{N}\sum_{i=1}^{N}\hat{u}_{i1}^2 Z_{i1}Z_{i1}' & \cdots & \frac{1}{N}\sum_{i=1}^{N}\hat{u}_{i1}\hat{u}_{iM}Z_{i1}Z_{iM}' \\ \vdots & \ddots & \vdots \\ \frac{1}{N}\sum_{i=1}^{N}\hat{u}_{iM}\hat{u}_{i1}Z_{iM}Z_{i1}' & \cdots & \frac{1}{N}\sum_{i=1}^{N}\hat{u}_{iM}^2 Z_{iM}Z_{iM}' \end{bmatrix}, \tag{8.19}$$

where the individual equations' $\hat{u}_{i,m}$ are based on consistent IV-based first stage estimates.[5] Thus, while single equation or equation-by-equation estimation assumes a block diagonal weighting matrix $\hat{V}^S = \mathrm{diag}(\sum_{i=1}^{N}\hat{u}_{i1}^2 Z_{i1}Z_{i1}', \ldots, \sum_{i=1}^{N}\hat{u}_{iM}^2 Z_{iM} \times Z_{iM}')$, the SGMM weighting matrix in (8.19) fully exploits cross error correlations in the residuals.[6]

8.2.4 Evaluation Literature on Finite Sample Performance

As Hayashi (2000) shows, joint estimation is asymptotically more efficient as long as at least one equation of the system is overidentified and the error terms are related to each other. However, the asymptotic results only hold if the model is correctly specified, that is, all the model assumptions are satisfied. Moreover, the asymptotic results may not be true for small samples (see Hayashi 2000). Unfortunately, no guidance is given in the literature with respect to the latter case.[7]

The only points of reference available are: 1) a rather small set of literature dealing with the relative efficiency of full versus limited information for the static panel data case (see Krishnakumar 1995, for an overview) as well as 2) a bulk of studies dealing with the empirical performance of single equation estimators for a dynamic panel data model. Here, a subset of the latter group also explicitly accounts for non-standard small N and small T data settings. The Monte Carlo simulation based studies reported in Kiviet (1995), Harris and Matyas (1996), Judson and Owen (1999), Islam (1999), Behr (2003), Hayakawa (2005), Soto (2009) and Lokshin (2008) among others generally show that the gains in efficiency terms of moving from parsimonious models to more complex representations with larger instrument sets (orthogonality conditions) are rather marginal in panel data settings with increasing T.

[5] In comparison to this, one-step estimation replace the first step residuals by an identity or related transformation matrix.

[6] Giving that certain assumptions hold, the SGMM approach reduces to the more familiar 3SLS notation. These assumptions are: Conditional homoscedasticity and identical instruments across equations. For details see e.g. Arellano (2003).

[7] The only notable exception known to the author for the simultaneous equation case is Binder et al. (2005). The authors take a Vector Autoregressive (VAR) perspective and compare GMM and quasi maximum likelihood (QMLE) based estimation. The results generally favor the QMLE approach; however, the authors also report good performance for the Blundell–Bond system estimator, while GMM in first differences generally performs weak.

GMM estimators of Arellano and Bond, Arellano and Bover, Ahn and Schmidt and Blundell and Bond are typically designed for panel data sets with large N and small T. According to Judson and Owen (1999) the associated loss in efficiency of instrument reduction from more advanced GMM techniques to the standard Anderson and Hsiao (1981) estimator is negligible for large T (approximately $T \geq 10$), while at the same time the 'many instruments problem' and computational difficulties associated with the large instrument sets are avoided. Indeed, Blundell and Bond (1998) themselves argue that their system GMM estimator is only appropriate for small T large N settings. An overview of the literature on the 'many instruments problem' is given, e.g., Hayakawa (2005).

Soto (2009) runs a simulation experiment to compare first difference, level and system GMM estimators in data settings where N is small compared to T (e.g. $N = 35$, $T = 12$), which comes much closer to the empirical setup in this study than the typical large N, small T assumption. His results show in terms of RMSE and standard deviation that, on average, the empirical fit of the first difference estimators is much lower compared to level and system counterparts. Though the latter estimator shows the best overall performance, the relative advantage to the level GMM estimator is rather marginal. If additionally the model is characterized by a high level of persistence in the autoregressive parameter (as it is typically the case in economic growth studies) the two estimators show an almost equal empirical performance. Similarly, comparing first difference, level and system GMM estimators, Hayakawa (2005) even finds that the system estimator has a more severe downward bias than the level estimator, if the variance of the individual effects (σ_μ) deviates from the variance of the remainder error term (σ_ν).[8]

The lack of simulation based guidance with respect to the proper estimator choice for a system of equation in small sample, contrasts its growing number of empirical applications: For example, in a series of papers Driffield and associates propose a FD-3SLS estimator, which generalizes the Anderson and Hsiao (1981) type approach to the system case (see e.g. Driffield and Girma 2003, Driffield and Taylor (2006) as well as Driffield and De Propris 2006). Moreover, Kimhi and Rekah (2005) apply an Arellano and Bond (1991) type estimator for a two equation system that explicitly accounts endogeneity and predeterminedness of right-hand side regressors. Finally, taking a time-series perspective both Di Giacinto (2010) as well as Alecke et al. (2010a) use full information estimation (FIML and Blundell–Bond based SGMM respectively) to specify VAR models with panel data.

In the following, we aim to bridge the gap between the growing number of empirical applications for dynamic panel data estimation in a system of equation and a systematic comparison of the small sample behavior for different estimation techniques. In order to do so, we set up a Monte Carlo simulation exercise to compare

[8]That is, for many regions of the α-coefficient of the lagged dependent variable (especially moderate and high value) and a $(\frac{\sigma_\mu}{\sigma_\nu}) = 0{,}25$ the level estimator displays the smallest bias among the estimators. This result indicates that the fact that the system estimator is a weighted sum of the FD and level estimator becomes a disadvantage of particular combinations for $(\frac{\sigma_\mu}{\sigma_\nu}) = 0{,}25$ and moderate high regions of the autoregressive parameter.

the finite sample performance of multiple equation extensions to a set of estimators, which are frequently applied in the single equation case. We compare the estimators regarding their bias and efficiency for standard large N, small T settings as well as for two-sided small samples. In subsequent steps we also control for model misspecifications in the error term such as heteroscedasticity.

8.3 Monte Carlo Simulations

8.3.1 Model Design and Parameter Settings

For the following Monte Carlo simulation exercise, we draw on a basic simulation setup proposed by Matyas and Lovrics (1990), who use a two-equation model with the endogenous variables $y1$ and $y2$ being defined in the following way:

$$y1_{i,t} = \alpha_0 + \alpha_1 y2_{i,t} + \alpha_2 y1_{i,t-1} + \alpha_3 x1_{i,t} + \mu 1_i + \nu 1_{i,t}, \tag{8.20}$$

$$y2_{i,t} = \beta_0 + \beta_1 y1_{i,t} + \beta_2 x2_{i,t} + \beta_3 x3_{i,t} + \mu 2_i + \nu 2_{i,t}. \tag{8.21}$$

The exogenous regressors $x1, x2, x3$ are generated by the following DGP:[9]

$$x1_{i,t} = \rho_1 x1_{i,t-1} + \psi 1_{i,t}, \tag{8.22}$$

$$x2_{i,t} = \rho_2 x2_{i,t-1} + \psi 2_{i,t}, \tag{8.23}$$

$$x3_{i,t} = \rho_3 x3_{i,t-1} + \psi 3_{i,t}. \tag{8.24}$$

In this setup outlined above, special attention has to be given to the proper specification of the error terms. Here we make the following definitions mostly in line with the recent mainstream body of Monte Carlo simulation work as

$$\nu 1_{i,t} \sim N(0, \sigma^2_{\nu 1}), \tag{8.25}$$

$$\nu 2_{i,t} \sim N(0, \sigma^2_{\nu 2}), \tag{8.26}$$

$$\mu 1_{i,t} \sim N_2(0, \Sigma_\mu), \tag{8.27}$$

$$\mu 2_{i,t} \sim N_2(0, \Sigma_\mu), \tag{8.28}$$

$$\psi 1_{i,t} \sim N(0, \sigma^2_{\psi 1}), \tag{8.29}$$

$$\psi 2_{i,t} \sim N(0, \sigma^2_{\psi 2}), \tag{8.30}$$

$$\psi 3_{i,t} \sim N(0, \sigma^2_{\psi 3}). \tag{8.31}$$

As in Arellano and Bond (1991) we use $\sigma^2_{\nu 1}$ and $\sigma^2_{\nu 2}$ as normalization parameters which we set equal to 1. Different from the time varying error term ν we model

[9]It is also possible to extend the basic setup in terms of endogenizing one or more $x_{i,t}$ variables with respect to the error term as $x_{i,t} = \rho x_{i,t-1} + \tau \mu_i + \theta \nu_{i,t} + \psi 1_{i,t}$ as, e.g., outlined in Soto (2009). However, for the remainder we set $\tau = 0$ and $\theta = 0$, which is standard in the Monte Carlo simulation based literature for single equation simulation models.

the unobservable individual effects μ as multivariate normally distributed to test whether a full information approach may enhance the estimator efficiency. The general distribution function for a set of p variables is denoted $N_p(a, \Sigma)$, where a is a $(p \times 1)$ vector of means and Σ is the $(p \times p)$ covariance matrix of the variables (see also Mooney 1997). We specify μ as multivariate normally distributed with zero mean and variance-covariance matrix according to

$$\Sigma_\mu = \begin{bmatrix} 1 & 0.8 \\ 0.8 & 1 \end{bmatrix}. \tag{8.32}$$

Throughout the Monte Carlo simulation experiment we also define a loading factor ξ determining the ratio of the two error components as $\xi = \frac{\sigma_\mu}{\sigma_\nu}$. This gives us the opportunity to test for the estimators' performance for different weighting schemes (as found, e.g., in Hayakawa 2005). While we keep some parameters constant ($\sigma_{\psi_i} = 0.9$; $\rho_i = 0.5$; $\beta_i = 0.5$), we modify the following parameters during the exercise: $\alpha_2 = (0.8; 0.5)$, which then also varies $\alpha_{1,3} = (1 - \alpha_2)$ in order to guarantee that a change in α_2 only affects the short-run dynamics between $x1$, $y2$ and $y1$; we also set $\xi = (0.5; 1; 4)$; $N = (15; 25; 50; 100)$ and $T = (5; 10; 15)$. With respect to the initial observations we proceed as follows: $y_{0,i} = 0$ and $x_{0,i} = 1/(1 - \rho)$. In line with Arellano and Bond (1991), for the DGP we set $T = T + 10$ and cut off the first 10 cross-sections so that the actual samples contain NT observations. The total number of repetitions is set to 1000 for each permutation in $y1$, $y2$, $u1$ and $u2$. The range of parameters gives a total set of 72 simulation designs, which are summarized in Table 8.1.

We test the different estimators in their limited and full information specification. Our primary interest rests on the empirical assessment of the different IV and GMM estimators defined above. Thus, we estimate one-step and two-step efficient versions of the DIF-SGMM, LEV-SGMM and BB-SGMM, respectively. The latter BB-SGMM is the Blundell–Bond type system estimator, combining information of the Arellano–Bond type DIF-SGMM and the orthogonality conditions for the level equation LEV-SGMM. Since the Anderson–Hsiao approach rests on standard IV specification, we construct the latter as AH-2SLS and AH-3SLS. Likewise, we also specify a FEM based IV approach, resulting in a FEM-2SLS and FEM-3SLS specification. As Cornwell et al. (1992) point out for the static simultaneous equation case, in the absence of assumptions about the individual effects, one cannot do better than applying efficient estimation (such as 3SLS) after a within transformation.

Since we know that the FEM model as λ-class estimator is biased in dynamic panel settings, we also aim to test for a bias corrected alternative, which has shown a good small sample performance in the single equation case (see, e.g., Kiviet 1995, 1999; Bun and Kiviet 2003; Bruno 2005). Unfortunately, no analytical bias corrected FEM estimator is available for the multiple equation case. We thus take a practical approach (as, e.g., proposed in Gerling 2002) and derive the bias correction from a single equation estimation and then set a parameter restriction for α_2 based on these results in an otherwise unrestricted system 3SLS approach.[10] One

[10] An alternative approach would be to rely on bootstrapped based bias correction as, e.g., outlined in Everaert and Pozzi (2007).

Table 8.1 Parameter settings in MC simulation designs

Design No.	T	N	ξ	α_2
1	5	25	0.5	0.8
2	5	25	1	0.8
3	5	25	4	0.8
4	5	50	0.5	0.8
5	5	50	1	0.8
6	5	50	4	0.8
7	5	100	0.5	0.8
8	5	100	1	0.8
9	5	100	4	0.8
10	5	250	0.5	0.8
11	5	250	1	0.8
12	5	250	4	0.8
13	5	25	0.5	0.5
...	...	...	...	...
14	5	25	1	0.5
...	...	...	...	...
25	10	25	0.5	0.8
...	...	...	...	...
49	15	25	0.5	0.8
...	...	...	...	...
...	...	...	...	...
72	15	250	4	0.5

drawback of the bias corrected FEM approach is that it is only valid for models with strictly exogenous regressors, which is violated in our case given the inclusion of $y2$ in (8.20) (see Bruno (2005b) for details).

An important modelling step for the regression approach is the choice of instruments for the respective estimators. Following Cornwell et al. (1992) and Ahn and Schmidt (1999) we assume that the same instruments are available for each structural equation. An aspect worth noting is that in the static case under the homoscedasticity assumption the asymptotic equivalence between 3SLS and GMM holds. However, Ahn and Schmidt (1999) have shown that this is not the case for the dynamic model using the full set of orthogonality conditions, in particular (8.9).[11]

Thus, using a GMM framework could potentially bring additional gains in efficiency, however at the same time the 'many instruments problem' may be present. Especially for sample settings with a small number of individuals this is a delicate point since the optimal weighting matrix in SGMM estimation has for each equation a rank of, at most, N. If the number of instruments exceeds N, the weighting matrix

[11] For the full argument see Ahn and Schmidt (1999).

is singular and no 2-step estimator can be computed. We thus keep the total number of instruments small.

We specify in total 16 limited and full information estimators with instruments for $y1_{i,t}$, $y1_{t,i-1}$ and $y2_{i,t}$ according to:[12]

- **FEM-2SLS** Within-type transformed model using contemporaneous and one period lagged information for $x1$ to $x3$ as instruments
- **FEM-3SLS** Instrument set as for FEM-2SLS, additional GLS-transformation
- **FEMc-2SLS** Instrument set as for FEM-2SLS, analytical bias correction up to order $O(1/NT^2)$
- **FEMc-3SLS** Instrument set as for FEM-2SLS, bias correction and GLS transformation
- **AH-2SLS** Anderson and Hsiao (1981) estimator using contemporaneous and one period lagged information for $x1$ to $x3$, twice lagged levels of $y1$ as instruments
- **AH-3SLS** Instrument set as for AH-2SLS, additional GLS-transformation
- **AB-GMM** One-step Arellano and Bond (1991) estimator using contemporaneous and one period lagged information for $x1$ to $x3$, all available lags for $y1$ as in (8.9)
- **AB-SGMM** Instrument set as for AB-GMM, two-step efficient weighting matrix as in (8.19)
- **LEV1-GMM** One-step level GMM estimation using contemporaneous and one period lagged information for $x1$ to $x3$
- **LEV1-SGMM** Instrument set as for LEV1-GMM, two-step efficient weighting matrix as in (8.19)
- **LEV2-GMM** One-step level GMM estimation using contemporaneous and one period lagged information for $x1$ to $x3$ and $\Delta y1_{t-1}$ according to (8.12)
- **LEV2-SGMM** Instrument set as for LEV2-GMM, two-step efficient weighting matrix as in (8.19)
- **BB1-GMM** One-step Blundell and Bond (1998) system GMM, instrument set as combination of LEV2-GMM and AH-IV
- **BB2-GMM** Instrument set as for BB1-GMM, two-step efficient weighting matrix as in (8.19)
- **BB1-SGMM** One-step Blundell and Bond (1998) system GMM, instrument set as combination of LEV2-GMM and AB-GMM
- **BB2-SGMM** Instrument set as for BB2-GMM, two-step efficient weighting matrix as in (8.19)

All estimators account for the endogeneity of $y1$, $y1_{t-1}$ and $y2$ based on valid instruments. The subset of 3SLS/SGMM estimators also accounts for the cross-equation error correlation. For estimator comparison we compute common evaluation criteria as *bias, standard deviation, root mean square error (rmse), NOMAD* and *NORMADSQD*. The bias for each regression coefficient ($\hat{\delta}$) is defined as

$$bias(\hat{\delta}) = \sum_{m=1}^{M} (\widehat{\delta_m} - \delta_{true})/M, \tag{8.33}$$

[12]Computations are made in Stata with selective use of the routines *ivreg2* (Baum et al. 2003), *xtlsdvc* (Bruno 2005c) and *xtabond2* (Roodman 2006).

where $m = (1, 2, \ldots, M)$ is the number of simulation runs. The rmse puts a special weight on outliers:

$$rmse(\hat{\delta}) = \sqrt{\left(\sum_{m=1}^{M} (\widehat{\delta_m} - \delta_{true})/M\right)^2}. \tag{8.34}$$

Extending the scope from a comparison of single variable coefficients to an analysis of overall measures of model bias and efficiency for the aggregated parameter space, we compute NOMAD and NORMSQD values, where the NOMAD (normalized mean absolute deviation) computes the absolute deviation of each parameter estimate from the true parameter, normalizing it by the true parameter and averaging it over all parameters as

$$NOMAD = \frac{1}{K}\sum_{k=1}^{K}\left[\frac{1}{M}\sum_{m=1}^{M}\left(\frac{|\widehat{\delta_{m,k}} - \delta_{true,k}|}{\delta_{true,k}}\right)\right]. \tag{8.35}$$

The NORMSQD computes the mean square error (mse) for each parameter, normalizing it by the square of the true parameter, averaging it over all parameters and taking its square root (for details see Baltagi and Chang 2000)

$$NORMSQD = \sqrt{\frac{1}{K}\sum_{k=1}^{K}\left[\frac{1}{M}\sum_{m=1}^{M}\left(\frac{(\widehat{\delta_{m,k}} - \delta_{true,k})^2}{\delta_{true,k}^2}\right)\right]}. \tag{8.36}$$

Both overall measures are thus straightforward extensions to the single parameter bias and rmse statistics defined above.

8.3.2 Simulation Results

Turning to the results, we evaluate the estimators' performance in different dimensions. In the single equation literature, most attention is spent on evaluating the estimators bias and efficiency for the autoregressive parameter α_2 of the endogenous variable $y1$. In order to have a reference value for our simulation design, we also focus on this parameter first. Thereby, our simulation results merely confirm the results given in the literature so far: As Fig. 8.1 shows for standard large N, small T settings ($N = 250$, $T = 5$, $\xi = 1$) and a high persistence in the autoregressive parameter $\alpha_2 = 0.8$, among the different full information estimators the LEV-SGMM and BB-SGMM specifications perform best in terms of bias from the true α_2-value. The box plots in Fig. 8.1 show that the distribution of estimates for the two LEV-SGMM and BB-SGMM estimators is very close to the true value of 0.8, while on top the LEV-SGMM models show an even smaller standard deviation. This results is also confirmed when comparing the estimators' rmse.[13]

[13]Detailed results for all estimated coefficients under the different parameter settings can be obtained from the author upon request.

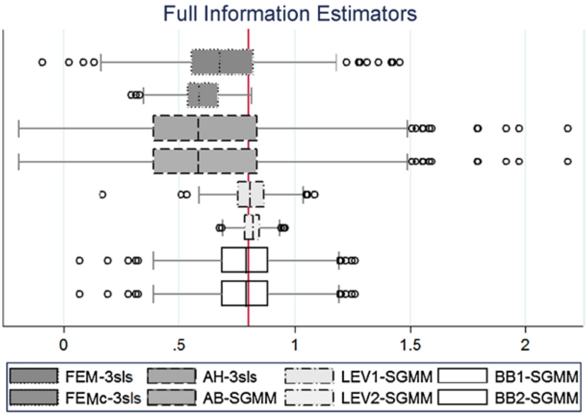


Fig. 8.1 $\hat{\alpha}_2$-simulation results with $N = 250$, $T = 5$, $\alpha_2 = 0.8$, $\xi = 1$

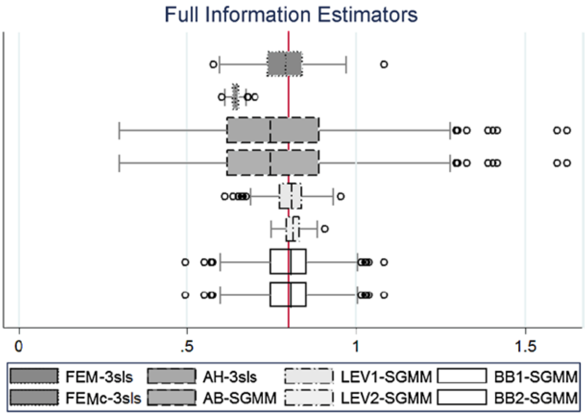


Fig. 8.2 $\hat{\alpha}_2$-simulation results with $N = 250$, $T = 15$, $\alpha_2 = 0.8$, $\xi = 1$

The latter difference in the rmse originates from the rather poor performance of the estimators in first differences (both the AH-3SLS as well as the AB-SGMM), which are significantly biased and show a large standard deviation around the true point estimate. If we recall from above that the Blundell–Bond estimator is a weighted average of the level and first difference specification, it becomes obvious that the poor performance of the first difference specifications also deteriorates the efficiency of the BB-SGMM model. The FEM and FEMc specification show a smaller standard deviation compared to the first difference specifications, however they also show a considerable bias. In the case of the FEMc this supports our argument from above that the bias correction may only work well for dynamic specifications with strictly exogenous regressors. The results hold qualitatively, if we increase the number of time periods to $T = 15$ in Fig. 8.2. We observe that with increasing time dimension the performance of all estimators—both in terms of bias and rmse—improves. Only the FEMc is still biased, which indicates that for equations with right hand side endogeneity beside the lagged autoregressive parameter of the dependent variable, the method performs rather weak, although it shows a very small variance.

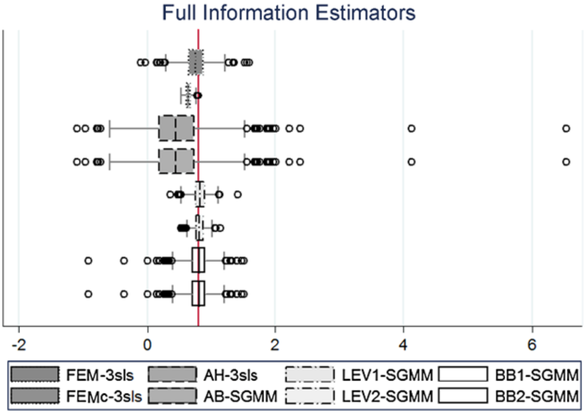


Fig. 8.3 $\hat{\alpha}_2$-simulation results with $N = 25$, $T = 15$, $\alpha_2 = 0.8$, $\xi = 1$

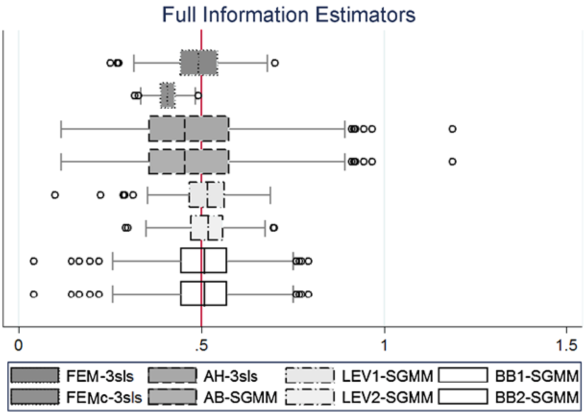


Fig. 8.4 $\hat{\alpha}_2$-simulation results with $N = 25$, $T = 15$, $\alpha_2 = 0.5$, $\xi = 1$

Moving from standard large N, small T panel data assumptions to simulation designs for two-sided small samples with both a small or moderate time and cross-section dimension, the results in Fig. 8.3 show for the case of $N = 25$, $T = 15$, $\xi = 1$ and $\alpha_2 = 0.8$ that the FD estimators (AH and AB) break down. Reducing the degree of persistence in the autoregressive parameter $\alpha_2 = 0.5$ however, leads to a significant improvement of the latter estimators (see Fig. 8.4). The best performances in terms of bias nevertheless are shown by the LEV-SGMM specifications. The FEM-3SLS also shows satisfactory small sample properties in two-sided small samples and moderate persistence in α_2. The performance of the latter estimator relative to the others is even increased, if we allow for a dominant share of the unobserved individual effects (μ_i) in the composition of the overall error term by setting $\xi = 4$. Here the FEM-3SLS outperforms all SGMM counterparts in terms of bias and efficiency (see Fig. 8.5).[14]

In order to compare the overall performance of the estimators, we finally compute ranking schemes for the absolute bias and the rmse with respect to α_2. The ranking

[14]Results for $\xi = 0.5$ are shown in Fig. 8.6.

Fig. 8.5 $\hat{\alpha}_2$-simulation results with $N = 25$, $T = 15$, $\alpha_2 = 0.5$, $\xi = 4$

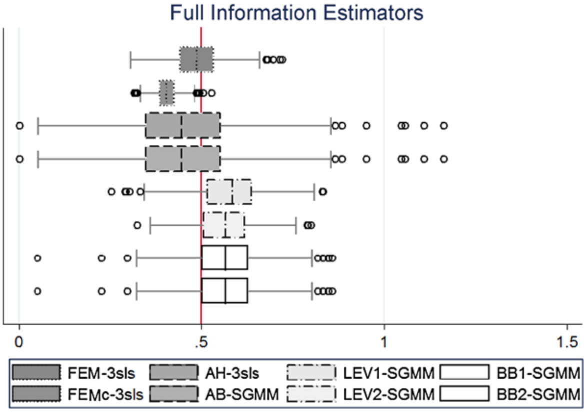
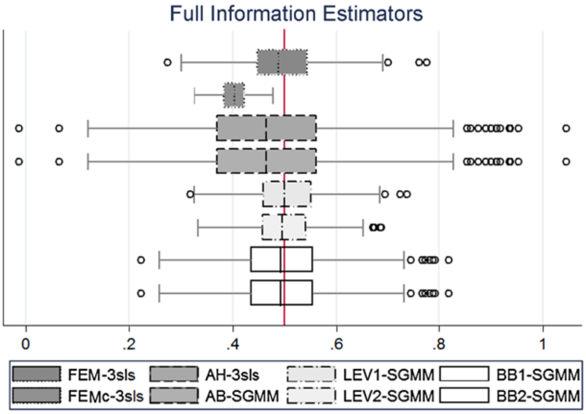


Fig. 8.6 $\hat{\alpha}_2$-simulation results with $N = 25$, $T = 15$, $\alpha_2 = 0.5$, $\xi = 0.5$



scheme is constructed as follows (for a similar approach see Lokshin 2008): For each parameter constellation we compute the absolute bias and rmse of each estimator. We then rank the estimator according to their relative performance and assign points in descending order. That is, in a first weighting scheme we give 16 points for the best estimator, 15 for the second best, 14 for the third and so forth. In order to price a superior performance, in a second weighting scheme we assign 10 points to the best estimator, 7 to the second best, 5 to the third, 3 to the fourth and 1 to the fifth best estimator. The results nevertheless show to be rather insensitive regarding the chosen weighting scheme. In the following, we thus only report results from scheme one, further results can be obtained upon request.

We present the average cumulative score for the different categories listed in Tables 8.2 and 8.3 defined as $\frac{1}{D}\sum_{i=1}^{D} P_i$, where D is the total number of simulation designs i considered and P_i is the number of points given to each estimator according to weighting scheme 1 with $P_i \in 1, \ldots, 16$. Looking the absolute bias, for almost all categories the two-step efficient BB-SGMM with instrument set 1 performs best. Also the limited information alternative BB1-GMM and both Blundell–Bond estimators using the larger instrument set 2 perform well. Second best are the LEV-GMM estimators, where again the system specification outranks the lim-

Table 8.2 Ranking of absolute bias for α_2

All		$\alpha_2 = 0.8$		$\alpha_2 = 0.5$	
BB1-SGMM	13.17	BB1-GMM	13.58	**BB1-SGMM**	12.78
BB1-GMM	12.82	**BB1-SGMM**	13.17	BB2-SGMM	11.81
BB2-SGMM	12.17	BB2-GMM	12.58	BB1-GMM	11.61
BB2-GMM	11.82	LEV1-SGMM	12.44	BB2-GMM	10.64
LEV1-SGMM	11.03	BB2-SGMM	12.17	LEV1-SGMM	9.33
LEV1-GMM	10.58	LEV1-GMM	11.94	LEV1-GMM	8.89
LEV2-SGMM	10.03	LEV2-SGMM	11.44	FEM-2sls	8.78
LEV2-GMM	9.58	LEV2-GMM	10.94	LEV2-SGMM	8.36
FEM-2sls	8.74	FEM-2sls	8.47	FEM-3sls	7.97
FEM-3sls	7.88	FEM-3sls	7.58	AH-GMM	7.94
AH-GMM	6.11	FEMc-2sls	5.00	LEV2-GMM	7.92
AH-SGMM	5.61	AH-GMM	4.11	AH-SGMM	7.89
AB-GMM	5.11	FEMc-3sls	4.00	AB-GMM	6.97
AB-SGMM	4.61	AH-SGMM	3.22	AB-SGMM	6.92
FEMc-2sls	3.88	AB-GMM	3.11	FEMc-2sls	2.69
FEMc-3sls	2.88	AB-SGMM	2.22	FEMc-3sls	1.72
No. of designs	72		36		36

$T = 5$		$T = 15$		$\xi = 4$	
BB1-SGMM	13.50	**BB1-SGMM**	13.00	**BB1-SGMM**	13.08
BB1-GMM	12.71	BB1-GMM	12.67	BB2-SGMM	12.08
BB2-SGMM	12.50	BB2-SGMM	12.00	BB1-GMM	11.54
LEV1-SGMM	11.92	BB2-GMM	11.67	FEM-2sls	11.25
BB2-GMM	11.71	LEV1-SGMM	10.50	BB2-GMM	10.54
LEV1-GMM	11.00	LEV1-GMM	10.17	FEM-3sls	10.50
LEV2-SGMM	10.92	FEM-2sls	10.04	AH-GMM	8.42
LEV2-GMM	10.00	LEV2-SGMM	9.50	LEV1-SGMM	8.33
FEM-2sls	7.33	FEM-3sls	9.29	AH-SGMM	7.58
FEM-3sls	6.17	LEV2-GMM	9.17	AB-GMM	7.42
AH-GMM	5.67	AH-GMM	6.50	LEV2-SGMM	7.33
FEMc-2sls	5.29	AH-SGMM	6.00	LEV1-GMM	7.17
AB-GMM	4.67	AB-GMM	5.50	AB-SGMM	6.58
AH-SGMM	4.67	AB-SGMM	5.00	LEV2-GMM	6.17
FEMc-3sls	4.29	FEMc-2sls	3.00	FEMc-2sls	4.50
AB-SGMM	3.67	FEMc-3sls	2.00	FEMc-3sls	3.50
No. of designs	24		24		24

Note: The average cumulative number of points is calculated as $\frac{1}{D}\sum_{i=1}^{D} P_i$, where D is the total number of simulation designs i considered and P_i is the number of points given to each estimator according to weighting scheme 1 with $P_i \in 1, \ldots, 16$

Table 8.3 Ranking of RMSE for α_2

All		$\alpha_2 = 0.8$		$\alpha_2 = 0.5$	
LEV1-SGMM	14.99	**LEV1-SGMM**	15.56	**LEV1-SGMM**	13.97
LEV2-SGMM	13.99	LEV2-SGMM	14.56	LEV2-SGMM	13.00
LEV1-GMM	13.58	LEV1-GMM	14.44	LEV1-GMM	12.33
LEV2-GMM	12.58	LEV2-GMM	13.44	FEM-2sls	11.61
BB1-GMM	10.13	BB1-GMM	10.89	LEV2-GMM	11.36
FEM-2sls	9.74	BB2-GMM	9.89	FEM-3sls	10.69
BB2-GMM	9.13	FEMc-2sls	8.89	BB1-GMM	9.08
FEM-3sls	8.93	BB1-SGMM	8.53	BB1-SGMM	8.86
BB1-SGMM	8.81	FEMc-3sls	7.89	BB2-GMM	8.11
FEMc-2sls	7.86	BB2-SGMM	7.53	BB2-SGMM	7.89
BB2-SGMM	7.81	FEM-2sls	7.53	FEMc-2sls	6.67
FEMc-3sls	6.86	FEM-3sls	6.86	FEMc-3sls	5.69
AH-GMM	4.28	AH-GMM	3.75	AH-GMM	4.69
AB-GMM	3.33	AB-GMM	2.81	AB-GMM	3.78
AH-SGMM	2.47	AH-SGMM	2.19	AH-SGMM	2.69
AB-SGMM	1.53	AB-SGMM	1.25	AB-SGMM	1.78
No. of designs	72		36		36

$T = 5$		$T = 15$		$\xi = 4$	
LEV1-SGMM	15.17	**LEV1-SGMM**	14.88	**LEV1-SGMM**	13.92
LEV2-SGMM	14.17	LEV2-SGMM	13.88	LEV2-SGMM	12.92
LEV1-GMM	13.75	LEV1-GMM	13.25	LEV1-GMM	12.08
LEV2-GMM	12.75	LEV2-GMM	12.25	LEV2-GMM	11.08
BB1-GMM	10.79	FEM-2sls	11.67	FEM-2sls	10.71
BB2-GMM	9.79	FEM-3sls	10.92	BB1-SGMM	10.04
FEMc-2sls	9.25	BB1-GMM	9.50	FEM-3sls	9.96
BB1-SGMM	9.04	BB1-SGMM	8.58	BB1-GMM	9.71
FEMc-3sls	8.25	BB2-GMM	8.50	BB2-SGMM	9.04
BB2-SGMM	8.04	BB2-SGMM	7.58	BB2-GMM	8.71
FEM-2sls	7.50	FEMc-2sls	6.75	FEMc-2sls	8.50
FEM-3sls	6.50	FEMc-3sls	5.75	FEMc-3sls	7.50
AH-GMM	4.08	AH-GMM	4.46	AH-GMM	4.38
AB-GMM	3.08	AB-GMM	3.54	AB-GMM	3.46
AH-SGMM	2.42	AH-SGMM	2.71	AH-SGMM	2.46
AB-SGMM	1.42	AB-SGMM	1.79	AB-SGMM	1.54
No. of designs	24		24		24

Note: The average cumulative number of points is calculated as $\frac{1}{D}\sum_{i=1}^{D} P_i$, where D is the total number of simulation designs i considered and P_i is the number of points given to each estimator according to weighting scheme 1 with $P_i \in 1, \ldots, 16$

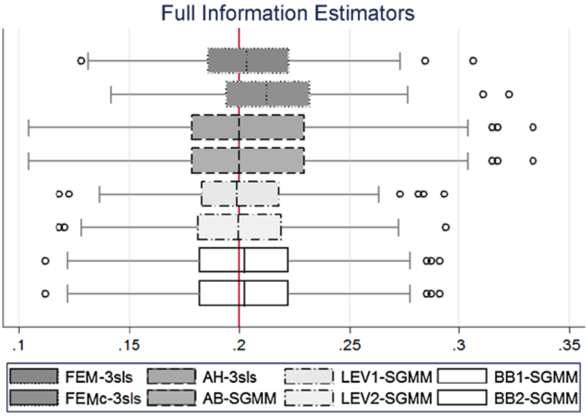


Fig. 8.7 $\hat{\alpha}_1$-simulation results with $N = 250$, $T = 15$, $\alpha_2 = 0.8$, $\xi = 1$

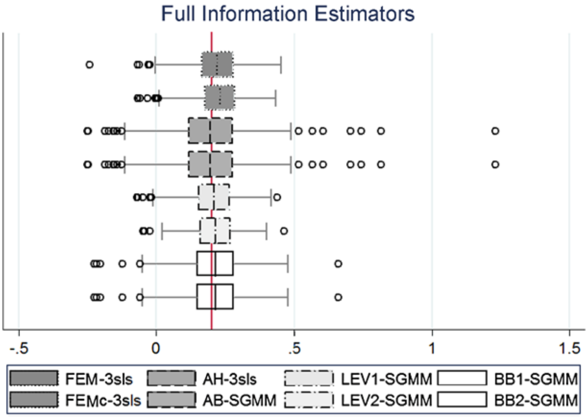


Fig. 8.8 $\hat{\alpha}_1$-simulation results with $N = 25$, $T = 15$, $\alpha_2 = 0.8$, $\xi = 1$

ited information alternative for most parameter constellations. Estimators based on the within-type and first difference transformation (AH and AB) follow with lower scores. With respect to the rmse in Table 8.3, the LEV1-SGMM specification outranks all other estimators. The first differenced estimators rank worst in this category, while the FEM-type models show on average a small comparably rmse.

In a system of equations with endogenous, predetermined and exogenous variables we are not only interested in inference on the autoregressive parameter α_2, but also care for performance of the respective estimators regarding all other coefficients. The ability to properly instrument the coefficients of the endogenous variables $y1$ and $y2$, which both enter as explanatory regressors, thus also matters. Looking at the bias and rmse error of the coefficients α_1 and β_1 respectively, the results for α_1 generally show that all estimators roughly perform equally well (see Figs. 8.7 and 8.8). However, this picture changes for the estimation of β_1, where the estimators in first differences perform poorly for most parameter constellations (and thus also affecting the quality of the Blundell–Bond type system estimator). The latter holds especially for small N settings as shown in Fig. 8.9. The results

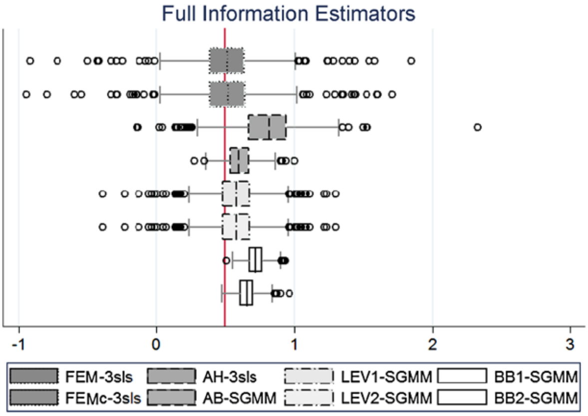


Fig. 8.9 $\hat{\beta}_1$-simulation results with $N = 25$, $T = 15$, $\alpha_2 = 0.8$, $\xi = 1$

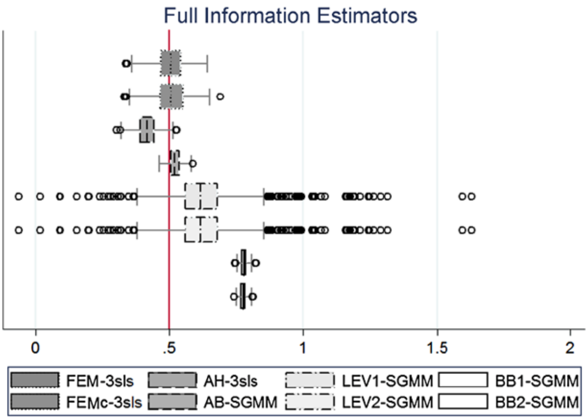


Fig. 8.10 $\hat{\beta}_1$-simulation results with $N = 250$, $T = 15$, $\alpha_2 = 0.8$, $\xi = 4$

indicate that properly instrumenting $y2$ based on transformations of the exogenous variables and predetermined endogenous variables is challenging.

When the error term is dominated by the unobserved individual effects with $\xi = 4$, both the LEV-GMM and BB-GMM specifications behave poorly (see Fig. 8.10). Here, estimation strategies that wipe out the individual effects either by the within-type transformation or by first differencing the data perform better. Looking at the joint ranking for bias and rmse in Tables 8.4 and 8.5, we see that the LEV-GMM specification (and also the SGMM alternative) is on average the preferred estimator (both overall as well as for specific parameter values). These results underline the relative estimators' performance for α_2. The FEM estimator indeed shows the best performance, when ξ is high, that is, when the overall error term is driven by the individual time-invariant effects μ. In general, the difference in the performance of the estimators is smaller compared to the results for α_2, which can be measured in terms of the difference in the average points allocated to the individual estimators for the parameter constellations shown in Tables 8.4 and 8.5.

Table 8.4 Ranking of absolute bias for α_1 and β_1

All		$\alpha_2 = 0.8$		$T = 5$		$\xi = 4$	
LEV2-GMM	11.69	LEV2-GMM	11.13	LEV1-GMM	11.69	FEM-2sls	11.40
LEV1-GMM	11.66	LEV1-GMM	10.99	LEV2-GMM	11.63	AH-GMM	10.79
LEV2-SGMM	11.32	LEV2-SGMM	10.88	LEV1-SGMM	11.10	AB-GMM	10.67
LEV1-SGMM	11.29	LEV1-SGMM	10.74	LEV2-SGMM	11.04	FEM-3sls	10.35
FEM-2sls	9.83	FEM-2sls	9.97	FEM-2sls	10.00	AH-SGMM	10.17
AB-GMM	8.99	AB-GMM	9.89	AB-GMM	9.27	AB-SGMM	9.85
FEM-3sls	8.91	AB-SGMM	9.67	FEM-3sls	8.58	LEV2-GMM	9.06
AB-SGMM	8.13	FEM-3sls	8.85	AB-SGMM	8.33	LEV1-GMM	8.92
FEMc-3sls	7.60	BB2-GMM	7.75	AH-GMM	8.29	LEV2-SGMM	8.88
BB2-SGMM	7.48	BB2-SGMM	7.26	AH-SGMM	8.04	LEV1-SGMM	8.73
BB2-GMM	7.44	FEMc-3sls	7.19	FEMc-3sls	7.92	FEMc-3sls	8.33
AH-GMM	6.96	AH-SGMM	7.07	BB2-SGMM	6.75	BB2-GMM	6.50
AH-SGMM	6.78	BB1-GMM	6.81	BB2-GMM	6.38	FEMc-2sls	6.46
BB1-GMM	6.48	AH-GMM	6.65	FEMc-2sls	6.19	BB1-GMM	6.15
FEMc-2sls	5.93	BB1-SGMM	5.63	BB1-GMM	5.88	BB2-SGMM	5.40
BB1-SGMM	5.53	FEMc-2sls	5.54	BB1-SGMM	4.92	BB1-SGMM	4.35
No. of designs	72		36		24		24

Note: The average cumulative number of points is calculated as $\frac{1}{D}\sum_{i=1}^{D} P_i$, where D is the total number of simulation designs i considered and P_i is the number of points given to each estimator according to weighting scheme 1 with $P_i \in 1, \ldots, 16$

Finally, in the multiple equation setting, we may further move up the level of aggregation and compare the overall performance of the various estimators. Here we use the NOMAD and NORMSQD extensions of the single parameter bias and rmse indicators. Figure 8.11 reports the NOMAD and NORMSQD values for standard $N = 250$, $T = 10$ settings with $\alpha_2 = 0.8$ and $\xi = 1$. As the figure shows, the absolute bias averaged over all parameter values is the smallest for the LEV-SGMM and the FEM-3SLS specifications. This result also holds for the NORMSQD computation in Fig. 8.12. As shown above, the estimators in first differences show the highest variance of estimates around the true parameter. To some extent this also has an impact on the efficiency of the Blundell–Bond type specifications. Basically the same results hold, if we reduce the number of cross sections to $N = 25$. Here, Fig. 8.13 for the NOMAD and Fig. 8.14 for the NORMSQD criterion show the following general picture: First, both the NOMAD and the NORMSQD increases. Second, the difference in terms of overall bias and efficiency between the best performing estimators (LEV-SGMM and FEM-3SLS) relative to the BB-SGMM and AB-SGMM shrinks.

Looking at the differences between the full and limited information approaches for different parameter settings, Fig. 8.15 (NOMAD) and Fig. 8.16 (NORMSQD) show that in two-sided small sample settings the gain in efficiency of the full information approach is rather marginal. As the figure shows for the parameter con-

Table 8.5 Ranking of absolute RMSE for α_1 and β_1

All		$\alpha_2 = 0.8$		$T = 5$		$\xi = 4$	
LEV1-SGMM	11.74	LEV1-SGMM	11.04	LEV1-SGMM	13.52	FEM-2sls	13.31
LEV2-SGMM	11.69	LEV2-SGMM	11.03	LEV2-SGMM	13.46	FEM-3sls	11.77
FEM-2sls	11.65	FEM-2sls	11.01	LEV1-GMM	12.27	FEMc-3sls	11.33
LEV1-GMM	10.76	FEMc-2sls	10.46	LEV2-GMM	12.21	FEMc-2sls	11.04
LEV2-GMM	10.71	LEV1-GMM	9.88	FEM-2sls	9.83	AH-GMM	9.85
FEM-3sls	10.22	LEV2-GMM	9.86	BB2-GMM	8.90	AB-GMM	9.29
FEMc-2sls	9.92	AB-GMM	9.40	FEMc-3sls	8.69	LEV1-SGMM	8.50
FEMc-3sls	9.11	FEM-3sls	9.21	BB1-GMM	8.42	LEV2-SGMM	8.46
BB2-GMM	7.94	BB2-SGMM	8.42	BB2-SGMM	8.10	AH-SGMM	7.71
BB2-SGMM	7.56	BB2-GMM	8.31	FEM-3sls	7.81	LEV1-GMM	7.52
AB-GMM	7.38	AB-SGMM	7.71	FEMc-2sls	6.79	LEV2-GMM	7.48
BB1-GMM	6.85	BB1-GMM	6.99	AB-GMM	6.19	AB-SGMM	7.38
AB-SGMM	5.79	FEMc-3sls	6.61	BB1-SGMM	6.08	BB2-GMM	6.29
BB1-SGMM	5.33	BB1-SGMM	6.07	AH-GMM	5.67	BB1-GMM	5.92
AH-GMM	5.19	AH-GMM	5.54	AB-SGMM	4.25	BB2-SGMM	5.75
AH-SGMM	4.17	AH-SGMM	4.47	AH-SGMM	3.81	BB1-SGMM	4.40
No. of designs	72		36		24		24

Note: The average cumulative number of points is calculated as $\frac{1}{D}\sum_{i=1}^{D} P_i$, where D is the total number of simulation designs i considered and P_i is the number of points given to each estimator according to weighting scheme 1 with $P_i \in 1, \ldots, 16$

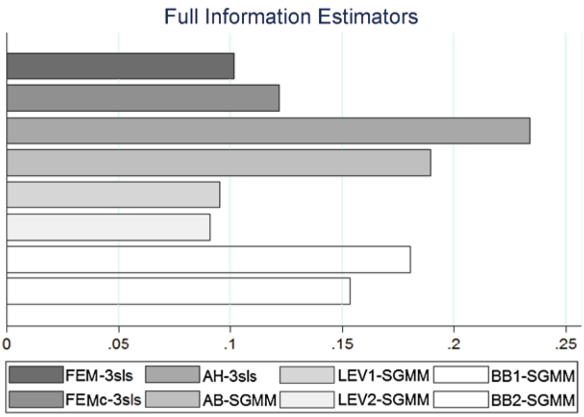


Fig. 8.11 NOMAD criterion for $N = 250$, $T = 10$, $\alpha_2 = 0.8$, $\xi = 1$

stellation $N = 25$, $T = 10$, $\alpha_2 = 0.8$ and $\xi = 1$, the limited information estimators perform at least equally well as their respective full information counterparts. However, when increasing the total number of observations in the sample, the relative performance of full versus limited information estimators increases as shown for the case of $N = 250$, $T = 10$ in Fig. 8.17 (NOMAD) and Fig. 8.18 (NORMSQD).

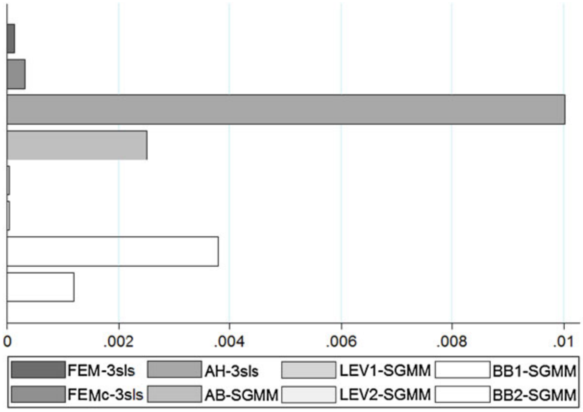


Fig. 8.12 NORMSQD criterion for $N = 250$, $T = 10$, $\alpha_2 = 0.8$, $\xi = 1$

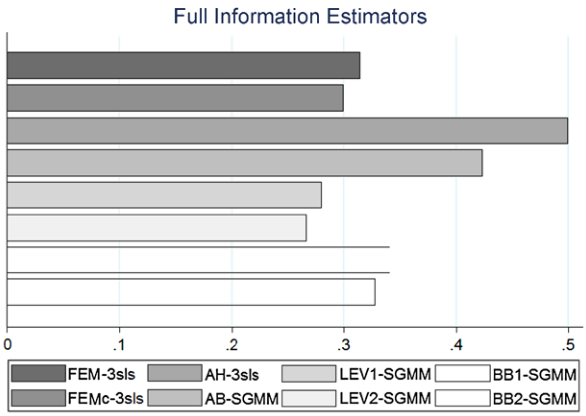


Fig. 8.13 NOMAD criterion for $N = 25$, $T = 10$, $\alpha_2 = 0.8$, $\xi = 1$

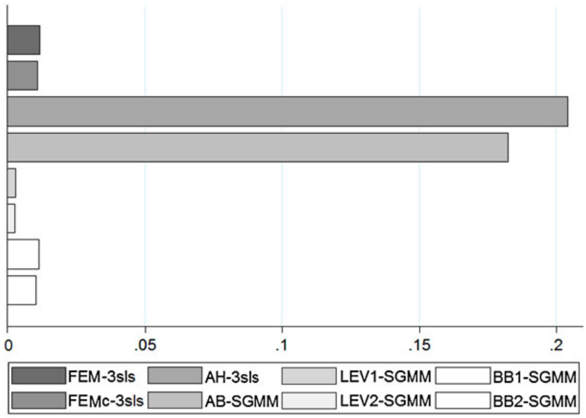


Fig. 8.14 NORMSQD criterion for $N = 25$, $T = 10$, $\alpha_2 = 0.8$, $\xi = 1$

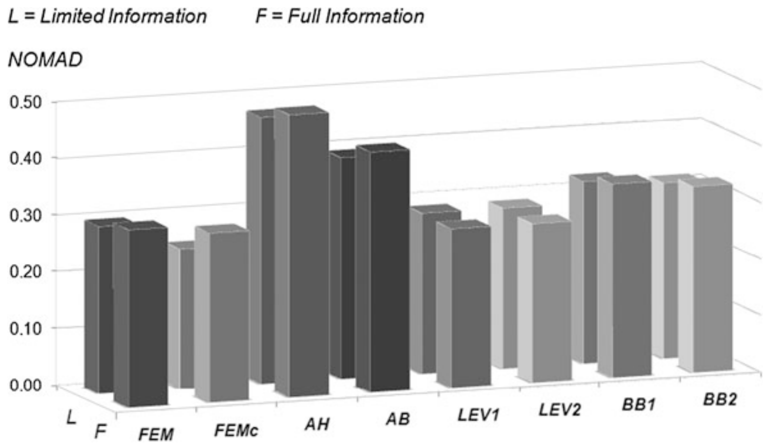


Fig. 8.15 NOMAD of full and limited information estimation for $N = 25$, $T = 10$

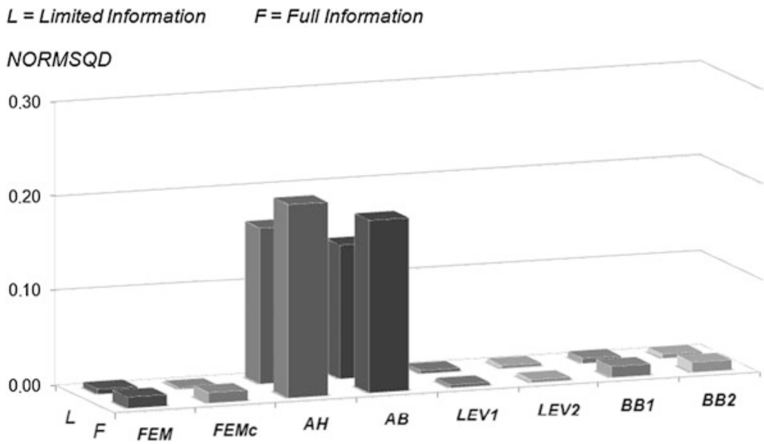


Fig. 8.16 NORMSQD of full and limited information estimation for $N = 25$, $T = 10$

Looking at the overall performance, Fig. 8.19 (for high persistence in the autoregressive parameter $\alpha_2 = 0.8$) and Fig. 8.20 (for $\alpha_2 = 0.5$) plot the percentage share of those cases, where the full information approach outranks the limited information counterpart for all estimated parameters with fixed $\xi = 1$. Both figures show that the relative superiority of the full system estimators increases, when both the time and cross-sectional dimension increases. However, only in rare cases the full information approaches show a better performance relative to the limited information counterparts (that is in more than 50% of cases for the respective parameter constellation, as indicated by the horizontal line in both figures). The results are in line with Soto (2009) for a comparison of one- and two-step efficient weighting matrices in the single equation case, where the author does not find large differences in the relative distribution. Similarly, Matyas and Lovrics (1990) report simulation

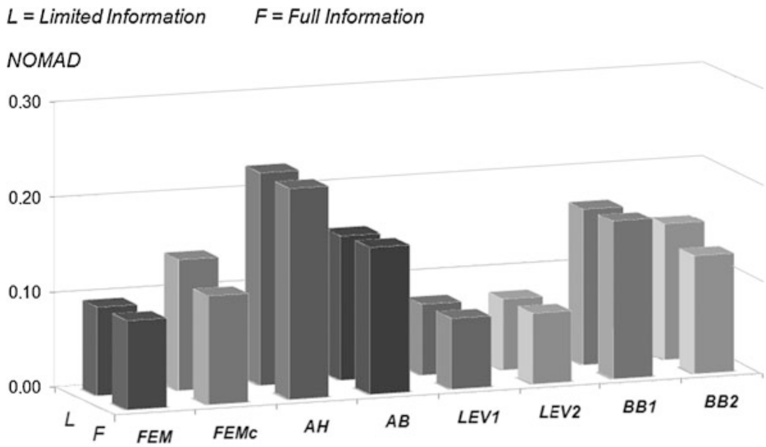


Fig. 8.17 NOMAD of full and limited information estimation for $N = 250$, $T = 10$

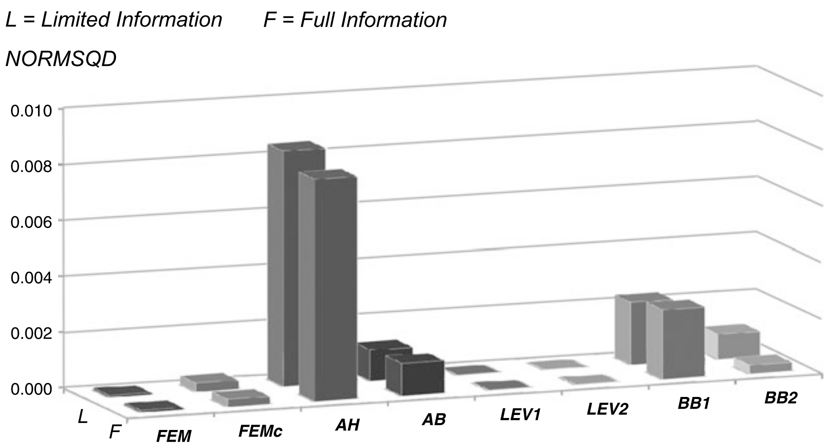


Fig. 8.18 NORMSQD of full and limited information estimation for $N = 250$, $T = 10$

results that favor OLS over the (generalized) G2SLS system estimator even for large samples with $N > 20$; $T > 20$.

This general picture is also reflected in the overall ranking of the estimators, shown in Tables 8.6 and 8.7 for the aggregation over all parameter constellations as well as different sub-categories. Here, the results lead to the following simple solution: For the parameter space employed in this Monte Carlo simulation exercise the simplest estimator is also the best: The FEM-2SLS ranks the best in terms of the NOMAD and has also a good second position regarding the NORMSQD criterion. This result particularly holds for a high parameter value of $\xi = 4$, that is, when the unobserved fixed effects make up a dominant part of the overall error term. However, there is also a second story to tell and that is, for various constellations with

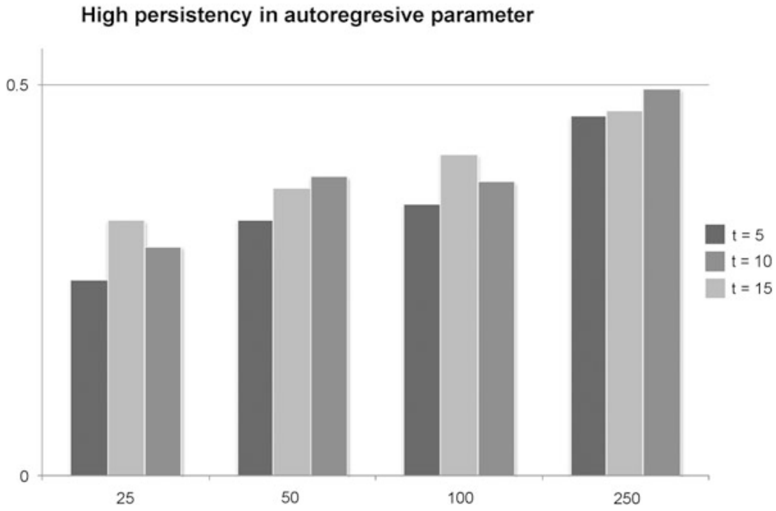


Fig. 8.19 Superiority of full and limited information estimation for $N \times T$ constellations with $\alpha_2 = 0.8$

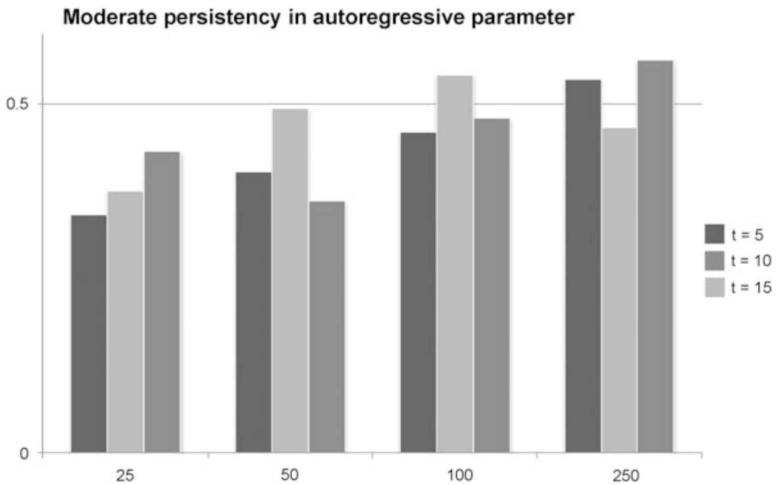


Fig. 8.20 Superiority of full and limited information estimation for $N \times T$ constellations with $\alpha_2 = 0.5$

a high persistence in the autoregressive parameter α_2 and a small time dimension, e.g. $T = 5$, the LEV-SGMM estimator performs best. This estimator also ranks best in terms of efficiency as measured by the NORMSQD criterion. While the latter two estimators may thus be seen as a good choice for empirical applications, when right-hand-side endogeneity and simultaneity matters, GMM based estimation techniques in first differences, which are still common tools in dynamic panel data setups, perform rather weak.

Table 8.6 Ranking of NOMAD for different parameter settings

All		$\alpha_2 = 0.8$		$T = 5$		$\xi = 4$	
FEM-2sls	12.81	*LEV1-SGMM*	13.53	*LEV1-SGMM*	13.46	**FEM-2sls**	14.00
LEV1-SGMM	12.53	LEV2-SGMM	12.50	LEV2-SGMM	12.13	FEMc-3sls	13.71
LEV2-SGMM	11.42	FEMc-2sls	12.11	LEV1-GMM	11.96	FEMc-2sls	13.13
FEM-3sls	11.35	LEV1-GMM	11.44	LEV2-GMM	10.88	FEM-3sls	12.67
FEMc-2sls	11.26	**FEM-2sls**	11.36	FEMc-3sls	10.29	AH-GMM	9.38
FEMc-3sls	10.94	FEMc-3sls	10.58	**FEM-2sls**	10.04	AB-GMM	8.71
LEV1-GMM	10.65	LEV2-GMM	10.42	FEMc-2sls	9.38	*LEV1-SGMM*	8.29
LEV2-GMM	9.63	FEM-3sls	9.56	BB1-GMM	8.46	AH-SGMM	7.96
BB2-SGMM	7.22	BB2-GMM	8.11	FEM-3sls	8.25	AB-SGMM	7.21
BB2-GMM	7.04	BB2-SGMM	7.53	BB2-SGMM	8.17	LEV2-SGMM	7.21
AB-GMM	6.36	BB1-GMM	6.64	BB2-GMM	8.00	LEV1-GMM	6.13
BB1-GMM	6.19	AB-GMM	6.11	BB1-SGMM	6.17	BB1-GMM	6.04
AB-SGMM	5.04	BB1-SGMM	5.56	AB-GMM	5.46	BB2-SGMM	5.96
BB1-SGMM	5.03	AB-SGMM	4.67	AH-GMM	5.33	BB2-GMM	5.38
AH-GMM	4.65	AH-GMM	3.42	AB-SGMM	4.04	BB1-SGMM	5.13
AH-SGMM	3.88	AH-SGMM	2.47	AH-SGMM	4.00	LEV2-GMM	5.13
No. of designs	72		36		24		24

Note: The average cumulative number of points is calculated as $\frac{1}{D}\sum_{i=1}^{D} P_i$, where D is the total number of simulation designs i considered and P_i is the number of points given to each estimator according to weighting scheme 1 with $P_i \in 1, \ldots, 16$

8.3.3 Extension: Simulation with Heteroscedastic Errors

So far we have assumed that the error terms are homoscedastic. In this section we alter this assumption. Our goal is to analyze whether the above obtained results also hold for heteroscedastic errors. As Bun and Carree (2005) point out, in data settings with large N and increasing T two types of heteroscedasticity (cross-section and time-series type) may be in order. For the scope of this analysis we focus on the cross-sectional case. As in Soto (2009) we therefore model the error terms $u1_{it}$ and $u2_{it}$ as uniformly distributed over the interval $U(0.5; 1.5)$.[15] We are specifically interested in investigating which consequences arise from the misspecification of the errors for estimators' empirical performance. Soto (2009) finds in Monte Carlo simulation designs for two-sided small samples that in the case of heteroscedasticity the variance and rmse of estimators increases, while the ranking of the alternatives is not affected. Generally, for large samples we expect that IV methods (2SLS/3SLS)

[15]Alternatively, one could follow Bun and Carree (2005), who propose to specify the variance as $\chi^2(1)$ distributed.

Table 8.7 Ranking of NORMSQD for different parameter settings

All		$\alpha_2 = 0.8$		$T = 5$		$\xi = 4$	
LEV1-SGMM	12.76	*LEV1-SGMM*	13.69	*LEV1-SGMM*	13.58	**FEM-2sls**	14.13
FEM-2sls	12.74	LEV2-SGMM	12.69	LEV1-GMM	12.25	FEMc-2sls	13.92
FEMc-2sls	11.72	FEMc-2sls	12.53	LEV2-SGMM	12.04	FEM-3sls	12.75
LEV2-SGMM	11.57	LEV1-GMM	11.83	LEV2-GMM	11.17	FEMc-3sls	11.58
FEM-3sls	11.10	**FEM-2sls**	11.03	FEMc-2sls	10.54	*LEV1-SGMM*	8.88
LEV1-GMM	11.07	LEV2-GMM	10.83	**FEM-2sls**	10.29	AH-GMM	8.46
LEV2-GMM	10.03	BB2-SGMM	9.22	FEM-3sls	8.96	LEV2-SGMM	7.75
FEMc-3sls	9.93	BB2-GMM	8.97	FEMc-3sls	8.96	BB1-GMM	7.50
BB2-SGMM	7.97	FEM-3sls	8.61	BB2-SGMM	8.63	BB2-SGMM	7.42
BB2-GMM	7.46	FEMc-3sls	8.58	BB1-GMM	8.25	AH-SGMM	7.21
BB1-GMM	6.56	BB1-GMM	7.56	BB2-GMM	8.17	LEV1-GMM	6.92
AB-GMM	5.53	BB1-SGMM	6.53	BB1-SGMM	6.33	BB2-GMM	6.79
BB1-SGMM	5.08	AB-GMM	5.06	AH-GMM	4.75	AB-GMM	6.33
AB-SGMM	4.32	AB-SGMM	3.89	AB-GMM	4.58	LEV2-GMM	5.88
AH-GMM	4.26	AH-GMM	2.78	AH-SGMM	4.25	BB1-SGMM	5.79
AH-SGMM	3.90	AH-SGMM	2.19	AB-SGMM	3.25	AB-SGMM	4.71
No. of designs	72		36		24		24

Note: The average cumulative number of points is calculated as $\frac{1}{D}\sum_{i=1}^{D} P_i$, where D is the total number of simulation designs i considered and P_i is the number of points given to each estimator according to weighting scheme 1 with $P_i \in 1, \dots, 16$

are still consistent but less efficient than GMM based estimators given that heteroscedasticity can be interpreted as cross-sectional correlation of arbitrary form.

The overall results for Monte Carlo simulations with heteroscedastic error terms are shown in Table 8.8 (NOMAD) and in Table 8.9 (NORMSQD). We focus on the same parameter settings as for the homoscedastic case. The tables show that the results basically hold for non-normal residuals, that is again FEM type and LEV-GMM specifications are the best choice in terms of bias and efficiency, respectively. On average the LEV1-SGMM estimator is the best choice except for model settings, where the error term is dominated by the unobserved individual effects. Here the bias corrected FEM estimator (both 2SLS as well as 3SLS) has the most favorable track record. Again, the estimators in first differences generally rank the lowest. Summing up, for non-normal errors there is no conflicting simulation evidence regarding the choice among different estimators relative to the homoscedastic case. Generally, FEM-type models, both full as well as limited information specification, show to be good estimators when consistency and efficiency of all regression coefficients matters. They outperform rival specifications in particular, when the share of the unobservable individual effects in the combined error term is large. Otherwise, and in particular if one is interested in capturing the time dynamics of the model properly, the LEV-SGMM is the preferred choice.

Table 8.8 Ranking of NOMAD for different parameter settings under heteroscedasticity

All		$\alpha_2 = 0.8$		$T = 5$		$\xi = 4$	
FEMc-2sls	10.56	LEV1-SGMM	14.19	LEV1-SGMM	11.50	FEMc-2sls	13.29
LEV1-SGMM	10.22	LEV2-SGMM	12.97	LEV2-SGMM	10.42	FEMc-3sls	12.33
FEM-2sls	10.17	LEV1-GMM	12.94	LEV1-GMM	10.21	FEM-2sls	12.21
LEV1-GMM	9.46	FEMc-2sls	11.72	BB2-GMM	9.58	AB-GMM	10.71
LEV2-SGMM	9.11	LEV2-GMM	11.72	BB1-GMM	9.54	FEM-3sls	10.50
AB-GMM	8.99	FEM-2sls	11.03	LEV2-GMM	9.13	AB-SGMM	8.88
FEMc-3sls	8.93	FEMc-3sls	10.22	FEMc-2sls	9.08	AH-GMM	8.79
BB2-GMM	8.88	FEM-3sls	8.69	AB-GMM	8.79	LEV1-SGMM	8.29
FEM-3sls	8.71	BB2-GMM	8.25	AH-GMM	8.54	AH-SGMM	7.63
LEV2-GMM	8.35	BB2-SGMM	7.97	FEMc-3sls	8.42	BB2-GMM	7.21
AH-GMM	7.89	BB1-GMM	7.42	BB2-SGMM	7.63	LEV2-SGMM	7.21
BB1-GMM	7.79	BB1-SGMM	6.22	FEM-2sls	7.13	LEV1-GMM	7.13
AB-SGMM	7.49	AB-GMM	5.06	AH-SGMM	7.08	BB1-GMM	6.25
AH-SGMM	6.96	AB-SGMM	3.67	BB1-SGMM	7.04	LEV2-GMM	6.04
BB2-SGMM	6.93	AH-GMM	2.19	AB-SGMM	6.92	BB2-SGMM	5.33
BB1-SGMM	5.58	AH-SGMM	1.72	FEM-3sls	5.00	BB1-SGMM	4.21
No. of designs	72		36		24		24

Note: The average cumulative number of points is calculated as $\frac{1}{D}\sum_{i=1}^{D} P_i$, where D is the total number of simulation designs i considered and P_i is the number of points given to each estimator according to weighting scheme 1 with $P_i \in 1, \ldots, 16$

8.4 Empirical Application: A Small-Scale Regional Economic Model

8.4.1 Model Specification

In this section we use the results from our Monte Carlo simulation experiment to estimate a small simultaneous equation model, which can be used for policy analysis. We are interested in estimating the effects of capital accumulation, both private as well as public, on regional economic growth. According to the public capital hypothesis, public capital is expected to have significant positive effects on private sector output, productivity and capital formation (see e.g. Wang 2002). Thus, public capital is assumed to enter directly and indirectly in the production process leading to q-complementary between public and private capital.[16] The latter concept of q-complementary implies that public investments are able to 'crowd-in' private

[16]In general, q-complementary and q-substitutability refers to the effect of the quantity of one resource on the marginal product of another source.

Table 8.9 Ranking of NORMSQD for different parameter settings under heteroscedasticity

All		$\alpha_2 = 0.8$		$T = 5$		$\xi = 4$	
LEV1-GMM	11.50	LEV1-GMM	13.19	LEV1-SGMM	12.25	FEMc-2sls	11.13
LEV1-SGMM	11.28	FEMc-2sls	12.92	LEV1-GMM	11.67	LEV1-SGMM	10.63
LEV2-GMM	10.17	LEV1-SGMM	12.72	BB1-GMM	11.50	LEV1-GMM	10.54
BB2-GMM	10.01	LEV2-GMM	11.44	BB2-GMM	11.17	BB2-GMM	10.04
LEV2-SGMM	9.94	LEV2-SGMM	10.97	LEV2-SGMM	11.00	BB1-GMM	10.00
BB1-GMM	9.93	FEM-2sls	10.94	LEV2-GMM	10.42	LEV2-SGMM	9.29
FEMc-2sls	9.53	FEMc-3sls	9.11	FEMc-2sls	8.38	LEV2-GMM	9.21
FEM-2sls	8.14	BB1-GMM	9.00	AB-GMM	8.13	FEM-2sls	9.04
AB-GMM	7.76	BB2-GMM	8.47	BB2-SGMM	8.13	AB-GMM	8.33
BB2-SGMM	7.38	FEM-3sls	8.47	BB1-SGMM	8.04	FEMc-3sls	7.96
AB-SGMM	7.03	BB2-SGMM	8.22	AH-GMM	7.67	AB-SGMM	7.50
BB1-SGMM	6.90	BB1-SGMM	7.75	AB-SGMM	6.83	AH-GMM	7.46
AH-GMM	6.75	AB-GMM	4.64	AH-SGMM	6.63	FEM-3sls	7.21
FEM-3sls	6.65	AB-SGMM	3.47	FEM-2sls	5.38	AH-SGMM	6.96
AH-SGMM	6.51	AH-GMM	2.47	FEMc-3sls	4.88	BB2-SGMM	5.58
FEMc-3sls	6.51	AH-SGMM	2.19	FEM-3sls	3.96	BB1-SGMM	5.13
No. of designs	72		36		24		24

Note: The average cumulative number of points is calculated as $\frac{1}{D}\sum_{i=1}^{D} P_i$, where D is the total number of simulation designs i considered and P_i is the number of points given to each estimator according to weighting scheme 1 with $P_i \in 1, \ldots, 16$

investment by increasing the rate of return to private capital and thereby stimulates economic growth. As Wang (2002) points out, public capital in terms of infrastructure can have three different effects on aggregate output. Firstly, it contributes directly as a measurable final product; secondly, as an intermediate input, and thirdly, as a source of positive externalities.

The latter link has been extensively studies in the field of the 'new growth' literature (see e.g. Barro 1990; Jones 2001; Barro and Sala-i-Martin 2003). Here, the mainstream approach in the literature typically starts from a standard Solow (1956) production function model, augmented by the inclusion of other productive factors in addition to private capital and labor. Besides the analysis of public capital, this model is also used to estimate the effect of fiscal policy on growth (see, e.g., Bajo-Rubio 2000). At the core of the model is a general production function of the form

$$Y = K^{\alpha} Z_1^{\beta_1} \cdots Z_m^{\beta_m} (AL)^{1-\alpha-\sum_{i=1}^{m}\beta_i} \left(\frac{KG}{K}\right)^{\gamma} \left(\frac{TR}{K}\right)^{\theta}, \tag{8.37}$$

where Y denotes output, K is private physical capital, Z_i with $i = 1, \ldots, m$ are other private inputs such as human or knowledge capital (see e.g. Lall and Yilmaz 2001),

L is labor and A is a labor augmenting factor. Additionally, KG and TR are government provided inputs as public physical capital and transfer payments, respectively. Equation (8.37) can be transformed in its intensive *per capita* formulation as

$$y = A\bar{k}^{\alpha}\bar{z_1}^{\beta_1}\cdots\bar{z_m}^{\beta_m}\left(\frac{KG}{K}\right)^{\gamma}\left(\frac{TR}{K}\right)^{\theta}, \tag{8.38}$$

with variables in small letters as *per capita* variables and the bar indicates *per capita* variables in efficiency units (such as $X : x = (X/L), \bar{x} = (X/AL)$). As Bajo-Rubio (2000) points out, the standard *per capita* production function exhibits decreasing returns to scale in both private capital and all private inputs. For empirical estimation in a cross-sectional (panel) analysis of countries or regions, the model in (8.38) is typically used in its standard empirical growth formulation (see e.g. Barro and Sala-i-Martin 1991, 1992, 2003) in log-levels as:

$$\begin{aligned}\log(y_{i,t}) - \log(y_{i,t-1}) = \text{const} - b \times \log(y_{i,t-1})&\\ + \sum_{j=0}^{1}\alpha_j \log(inv_{i,t-j}) + \sum_{j=0}^{1}\beta_j \log(n+g+\delta)_{i,t-j}&\\ + \sum_{j=0}^{1}\gamma_j \log(pub_{i,t-j}) + \Psi'\mathbf{Z} + u_{i,t},&\end{aligned} \tag{8.39}$$

where $i = 1, \ldots, N$ is the cross-sectional dimension and $t = 1, \ldots, T$ is the time dimension. The dependent variable y_{it} is defined as output per employee for region i and time period t, $y_{i,t-1}$ is the one-period lagged observation. Next to its own lagged value, the model includes current and (one-period) lagged values of the following factor inputs as right-hand side regressors: $inv_{i,t}$ is the private sector investment rate, $n_{i,t}$ is the labor force growth rate, g and δ are exogenous technical change and depreciation, $pub_{i,t}$ is the public sector investment rate. $\mathbf{Z}$ is a vector of further growth determinants including factors such as human capital or public transfer payments, u_{it} is the error term and b, α, β, γ, δ, ϕ, ω and Ψ are coefficients to be estimated.[17]

The model in (8.39) assumes that causality runs from private and public inputs to output growth. However, as Wang (2002) summarizes the recent empirical literature, evidence remains ambiguous as to whether a significant positive correlation indicates that public infrastructure raises private output, or whether in turn a rise in private output raises the demand for public infrastructure. Thus, the direction of causality is a priori not clear (see also Holtz-Eakin 1994). To account for the likely existence of two-way causality, in empirical estimation, we will use (8.39) and add further equations for the factor inputs of private and public investment. By accounting for the endogeneity of the two factor inputs we are able to explicitly channel the relationship between the variables in the core model and are better equipped for

[17] The inclusion of lagged income growth in (8.39) measures, whether convergence forces among the i cross-sectional units are at work (implying a negative regression coefficient b).

opening up the system to conduct regional policy analysis in an augmented setup. Some of the likely gains associated with this system approach compared to the single equation estimation are as follows:[18] First, the role of the policy variables in the system can be interpreted more meaningful. That is, the indirect effects of regional policies on the production function are modelled via the endogenized factor inputs, so the policy variables in the growth equation are left to determine the effect on total factor productivity in isolation.

Second, by addressing potential right-hand-side endogeneity and cross-equation residual correlation, this setup may generally result in consistent and more efficient parameter estimates compared to the single equation approach. By using appropriate instrumental variables for endogenous right-hand side variables in the system approach, the single parameters are estimated consistently (see e.g. Bond et al. 2001, with a reference to growth model estimates), further the system approach leads to more efficient results, especially if there is a non-zero covariance matrix of the error terms (see Greene 2003).

We can thus set up a small-scale 3-equation system using a partial adjustment framework, which is formulated as a simple dynamic process with time lag according to

$$\begin{bmatrix} \Delta y^*_{i,t} \\ inv^*_{i,t} \\ pub^*_{i,t} \end{bmatrix} = \begin{bmatrix} inv^*_{i,t}, & pub^*_{i,t}, & \mathbf{Z} \\ \Delta y^*_{i,t}, & pub^*_{i,t}, & \mathbf{Z} \\ \Delta y^*_{i,t}, & inv^*_{i,t}, & \mathbf{Z} \end{bmatrix} + \begin{bmatrix} u1_{i,t} \\ u2_{i,t} \\ u3_{i,t} \end{bmatrix}, \tag{8.40}$$

where "*" denote the equilibrium level for a variable x. Δ is the difference operator defined as $\Delta y_{i,t} = \log(y_{i,t}) - \log(y_{i,t-1})$. The equilibrium level is assumed to be connected to actual current and past observations of x as

$$\log(x_{i,t}) - \log(x_{i,t-1}) = \eta \log(x^*_{i,t}) - \eta \log(x_{i,t-1}) \tag{8.41}$$

and solving for $x^*_{i,t}$ yields:

$$\log(x^*_{i,t}) = \frac{1}{\eta} \log(x_{i,t}) + \log(x_{i,t-1}), \tag{8.42}$$

where η can be interpreted as the speed of adjustment parameter for variable x. Substituting this equation for each $x^*_{i,t}$ in the equation system of (8.40) yields for each equation a relationship for estimation with only observable variables, since equilibrium values are substituted by current and one-period lagged observed values for the respective variable. Alternatively, we also estimate specifications which solely depend upon lagged values.

We apply the 3-equation system of output growth (Δy), private capital investment (*inv*) and public capital investment (*pub*) for German regions (NUTS1 level) since re-unification. As Uhde (2009) points out, the investigation of economic effects arising from public infrastructure and transfer payments is still rarely analyzed at the regional and federal state level in Germany. The next section briefly outlines

[18] See e.g. Ulubasoglu and Doucouliagos (2004) for a further discussion.

the dataset. Empirical results for the baseline model as well as augmented specifications including interregional spillover effects from public capital and regional policy variables are presented subsequently.

8.4.2 Data and Empirical Results for Baseline Model

For the empirical estimation we use panel data for the 16 German states between 1991 and 2006 (total 256 observation). All monetary variables are denoted in real terms with base year 2000 (in Euro). If no specific price indices are available, the GDP deflator is used to deflate the series. A detailed description of the variables and source is given in Table 8.10. Besides the three main variables $\Delta y_{i,t}$, $inv_{i,t}$ and $pub_{i,t}$ we use a set of control variables to serve as (excluded) instruments for the system estimation. The latter comprises the population level, unemployed persons, human capital, the share of manufacturing sector in total regional output as well as the regional ex-ante tax base.

Since we are dealing with a moderate time dimension $T = 16$, non-stationarity of the data—and thus spurious regression—may be an issue. We therefore perform a set of panel unit root tests for the main variables in our 3-equation system. The results are reported in Table 8.11. We use test statistics proposed by Im et al. (2003) and Pesaran (2007), respectively. The advantage of the latter is that the test is robust with respect to cross-sectional correlation of the variables in focus. Since we are dealing with regional entities, cross-sectional interdependency cannot be excluded per se.

As the results of both the IPS as well as Pesaran's CADF test show, for output growth and public capital investments the null hypothesis of non-stationarity in $\Delta y_{i,t}$, $inv_{i,t}$ and $pub_{i,t}$ can clearly be rejected for reasonable confidence levels. For private investments, both tests are only able to reject the null hypothesis at the 10 percent significance level, giving weak support that the variable may be integrated. However, taken together with our ex-ante theoretical expectations that output and private/public capital are typically found to be integrated of order $I(1)$, while their growth rates (that is investments) are difference stationary respectively, we treat all variables as stationary and include them in our 3-equation system.

Turning to the regression results, we first estimate the baseline 3-equation system using different limited and full information approaches. Guided by the MC based small sample evidence above, we focus on FEM and LEV-GMM based alternatives. We start with the limited information approach, which accounts for the endogenous variables of the system by appropriate instruments but ignores cross equations residual correlations (as done in the full information approach). The results are presented in Table 8.12. As the results show, the IV-based FEM and LEV-GMM approaches yield qualitatively similar results for all three equations.

For output growth, both estimation techniques report only a moderate coefficient for the included lagged endogenous variable, there is a positive contemporaneous correlation between GDP growth and both private as well as public investment rates. However, the lagged variable coefficients turn out to be significantly negative and al-

Table 8.10 Data description and sources

Variable name	Description	Source
y_{it}	Output per employee, 1000 EUR, in real terms (base year 2000)	VGR der Länder (VGRdL 2009)
inv_{it}	Private sector investment rate as gross fixed capital formation per employee, in real terms	VGRdL (2009)
pub_{it}	Public sector investment rate as ratio of public investment relative to total regional government spendings	Council of Economic Advisors (SVR 2009)
Exogenous control variables		
$(n+g+\delta)_{it}$	Employment growth plus constant term (0.05)	VGRdL (2009); own calculations
hc_{it}	Human capital as a weighted composite indicator from 1) high school graduates with university qualification per total population between 18–20 years (*hcschool*), 2) number of university degrees per total population between 25–30 years (*hcuni*), 3) share of employed persons with university degree relative to total employment (*hcsvh*), 4) number of patents per populations (*hcpat*)	Destatis (2008a, 2008b), Federal Employment Agency (2009), DPMA (2008), own calculations
$unemp_{it}$	Total number of unemployed persons	Federal Employment Agency (2009)
$IS_{i,t}$	Share of industry sector GVA relative to total GVA	VGRdL (2009), own calculations
τ_{it}	Total regional tax volume (ex ante) as share of regional GDP	Destatis (2009c), own calculations
nmr_{it}	Net migration (in- minus out-migration) per population	Destatis (2009d), own calculations
pop_{it}	Population	VGRdL (2009)
East	(0, 1)-Dummy for East Germany	Own calculations
Interregional spillovers from public capital		
$Wpub_{it}$	Distance weighted average of public sector investments for regions j with $j \neq i$	SVR (2009), own calculations
$Wpubtrans_{it}$	Distance weighted average of public sector investments in transport infrastructure for regions j with $j \neq i$ (machinery & equipment, buildings & construction in transport and communication networks)	DIW (2000), own calculations
$Wpubscience_{it}$	Distance weighted average of public sector investments in science infrastructure for regions j with $j \neq i$ (machinery & equipment, buildings & construction for universities and public research facilities)	DIW (2000), own calculations
Regional policy transfers		
LFA_{it}	Federal government and interstate redistribution transfers per capita, in real terms	BMF (2009a, 2009b), own calculations
GRW_{it}	Federal transfers to private sector and business related infrastructure per employee, in real terms	BAFA (2008), own calculations

Table 8.11 Panel unit root tests for variables in the 3-equation system

Variable	IPS and CADF t-bar test $N, T = 16, 16$ H_0: Series non-stationary			
	W[t-bar]	No. of lags	Z[t-bar]	No. of lags
$\Delta y_{i,t}$	-8.29^{***}	0.88	-4.94^{***}	1
$inv_{i,t}$	-1.59^{*}	1.75	-1.57^{*}	1
$pub_{i,t}$	-6.78^{***}	1.38	-3.03^{***}	1

Note: For the IPS test, the average number of lags included has been determined according to the Akaike information criterion (AIC). The set of excluded instruments for the endogenous current and predetermined variables contains current and one period lagged values of: $\tau_{i,t}$ $IS_{i,t}$, $nmr_{i,t}$ and $unemp_{i,t}$ (all in log-levels). For the LEV-GMM also variable transformations based on the stationarity moment condition are used
*Denote statistical significance at the 10% level **Denote statistical significance at the 5% level
***Denote statistical significance at the 1% level

Table 8.12 Limited information DSEM estimation for $\Delta y_{i,t}$, $inv_{i,t}$ and $pub_{i,t}$

Model:	FEM-2SLS	LEV-GMM	FEM-2SLS	LEV-GMM	FEM-2SLS	LEV-GMM
Dep. var.:	$\Delta y_{i,t}$	$\Delta y_{i,t}$	$inv_{i,t}$	$inv_{i,t}$	$pub_{i,t}$	$pub_{i,t}$
$\Delta y_{i,t}$			1.62^{***}	1.86^{*}	1.03^{**}	3.09^{***}
			(0.509)	(1.016)	(0.461)	(0.515)
$inv_{i,t}$	0.24^{***}	0.20^{***}			0.20	-0.41^{*}
	(0.069)	(0.049)			(0.194)	(0.223)
$pub_{i,t}$	0.19^{**}	0.22^{***}	0.25	-0.47^{*}		
	(0.088)	(0.042)	(0.274)	(0.276)		
$\Delta y_{i,t-1}$	0.18^{*}	0.26^{***}	0.37	0.42	-0.54^{***}	-1.10^{***}
	(0.096)	(0.093)	(0.281)	(0.723)	(0.200)	(0.278)
$inv_{i,t-1}$	-0.22^{***}	-0.22^{***}	0.81^{***}	0.96^{***}	-0.08	0.48^{**}
	(0.053)	(0.045)	(0.043)	(0.064)	(0.164)	(0.226)
$pub_{i,t-1}$	-0.17^{***}	-0.14^{***}	-0.01	0.25	0.49^{***}	0.81^{***}
	(0.044)	(0.048)	(0.168)	(0.263)	(0.074)	(0.062)
N	240	240	240	240	240	240
Time dummies	yes	yes	yes	yes	yes	yes
R^2	0.69	0.71	0.77	0.77	0.67	0.87
ξ	0.35		1.07		1.81	
χ^2_{het}	32.4 ($p = 0.14$)		33.8^{*} ($p = 0.08$)		30.4 ($p = 0.21$)	

Note: ξ is the ratio of the two error components μ and ν, χ^2_{het} is the Pagan and Hall's (1983) test of heteroscedasticity for instrumental variables (IV) estimation. External instruments used are current and one-period lagged values of: τ_{it}, $unemp_{it}$, nmr_{it} and IS_{it}
*Denote statistical significance at the 10% level **Denote statistical significance at the 5% level
***Denote statistical significance at the 1% level

most of equal sign, so that the partial long-run effect from each variable are mostly tested to be insignificant, except for public capital investments in the LEV-GMM specification with a statistically significant long-run elasticity of 0.09 (standard error: 0.013).[19]

For both the private and public investment rate the degree of autocorrelation is found to be much higher. Besides this, output growth has a positive effect on both variables. In the equation for public investment, the FEM specification also finds a statistically significant long-run elasticity of private investment of 0.23 (standard error: 0.077), which gives first empirical support for q-complementary between the variables. Also in the LEV-GMM model lagged private investments turn out to be statistically significant and of expected positive sign, however, given that current investment enter the equation with a negative sign, the long-run elasticity (0.39, standard error: 0.288) turns out to be statistically insignificant in this specification.

The estimated specifications show a rather good fit with values of R^2 ranging between 0.70 and 0.90. For none of the models we detect any sign of heteroscedasticity in the error terms. However, the fraction of the unobservable individual effects relative to the remainder error component may become quite large (about two, in the case of $pub_{i,t}$). In these settings, the FEM based alternatives have shown the best performance in our Monte Carlo simulation exercise. We thus focus on fixed effects model, when turning to the full information estimation.

The results for the Panel DSEM in its FEM-3SLS specification are reported in Table 8.13. While the estimated regression coefficients remain rather stable relative to the limited information approach, we get strong empirical evidence that full information approach enhances the estimation efficiency. That is, the residuals from the first stage 2SLS regression show a significant cross-equation correlation in all cases. This result is also supported by a Harvey–Phillips (1982) type exact independence test, which checks for the joint significance of the other equations' residuals in an augmented first step regression (see e.g. Dufour and Khalaf 2002, for details). In all cases, the null hypothesis of insignificance is clearly rejected.

Finally, to compare the 2SLS and 3SLS estimators with respect to estimation efficiency, we employ the Hausman (1978) m-statistic, which is defined as:

$$m = \hat{q}'(\hat{Q} - \hat{V})^{-1}\hat{q}, \tag{8.43}$$

where $\hat{q} = \hat{\beta}_{3SLS} - \hat{\beta}_{2SLS}$ is the difference between the 3SLS and 2SLS estimators of the same parameter, $\hat{Q}$ and $\hat{V}$ denote consistent estimates of the asymptotic covariance matrices of $\hat{\beta}_{3SLS}$ and $\hat{\beta}_{2SLS}$ respectively. The m-statistic has a χ^2 distribution with degrees of freedom equal to the number of parameter estimates. The underlying idea of the test is quite simple: Under the assumption that the 3SLS estimator is generally more efficient than the 2SLS estimator, we test whether the difference between the estimators is large, indicating that the more complex GLS transformation in the 3SLS case induced a misspecification in the model which renders it inconsistent. Thus, under the null hypothesis, both estimators are consistent but only $\hat{\beta}_{3SLS}$

[19]Computation of the partial long-run elasticity is based on the delta method, where the long-run effect for $pub_{i,t}$ is calculated as $[(pub_{i,t} + pub_{i,t-1})/(1 - \Delta y_{it-1})]$.

Table 8.13 Full information DSEM estimation for $\Delta y_{i,t}$, $inv_{i,t}$ and $pub_{i,t}$

Model:	Panel DSEM		
Dep. var.:	$\Delta y_{i,t}$	$inv_{i,t}$	$pub_{i,t}$
$\Delta y_{i,t}$		2.33***	1.16***
		(0.211)	(0.297)
$inv_{i,t}$	0.39***		−0.35**
	(0.036)		(0.157)
$pub_{i,t}$	0.41***	−0.67***	
	(0.113)	(0.336)	
$\Delta y_{i,t-1}$	−0.11	0.28	0.18
	(0.088)	(0.218)	(0.193)
$inv_{i,t-1}$	−0.36***	0.89***	0.37***
	(0.028)	(0.040)	(0.128)
$pub_{i,t-1}$	−0.28***	0.52**	0.59***
	(0.071)	(0.201)	(0.071)
N	240	240	240
Time dummies	yes	yes	yes
$\|m\|$-stat.	4.96	9.41	11.66
	(0.99)	(0.97)	(0.94)
$\chi^2(2)_{HP}$	93.81	972.26	544.26
	(0.00)	(0.00)	(0.00)

	$u_{\Delta y}$	u_{inv}	u_{pub}
$u_{\Delta y}$	1.00		
u_{inv}	−0.92***	1.00	
u_{pub}	−0.51***	0.26***	1.00

Note: $|m|$-stat. is the absolute value of the Hausman m-statistic. $\chi^2(2)_{HP}$ reports the Harvey–Phillips (1982) type independence test for cross-equation residual correlation. External instruments used are current and one-period lagged values of: τ_{it}, $unemp_{it}$, nmr_{it} and IS_{it}

*Denote statistical significance at the 10% level

**Denote statistical significance at the 5% level

***Denote statistical significance at the 1% level

is efficient. Under the alternative hypothesis only $\hat{\beta}_{2SLS}$ is consistent.[20] The results of the Hausman $|m|$-statistic in Table 8.13 show that for all equations the null hypothesis cannot be rejected for reasonable confidence levels, giving strong support for the 3SLS compared to the 2SLS results.

The estimated FEM-3SLS model in Table 8.13 may be seen as the standard DSEM approach adapted to dynamic panel data settings in regional economics. However, as Rickman (2010) points out, this approach of structural modelling has recently been criticized for various reasons. One argument is the rather ad-hoc clas-

[20]By construction, if the 2SLS variance is larger than the 3SLS variance, the test statistic will be negative. Though the original test is not defined for negative values, here we will follow Schreiber (2007) and take the absolute value of the m-statistics as indicator for rejecting the null hypothesis of 3SLS efficiency.

Table 8.14 Full information PVAR estimation for $\Delta y_{i,t}$, $inv_{i,t}$ and $pub_{i,t}$

Model:	PVAR(1)			PVAR(2)		
Dep. var.:	$\Delta y_{i,t}$	$inv_{i,t}$	$pub_{i,t}$	$\Delta y_{i,t}$	$inv_{i,t}$	$pub_{i,t}$
$\Delta y_{i,t-1}$	0.64***	1.51***	0.39***	0.84***	1.60***	0.40**
	(0.049)	(0.161)	(0.109)	(0.065)	(0.225)	(0.155)
$inv_{i,t-1}$	−0.07***	0.68***	0.03	−0.15***	0.52***	−0.01
	(0.011)	(0.036)	(0.024)	(0.016)	(0.055)	(0.038)
$pub_{i,t-1}$	0.06***	0.29***	0.55***	0.02	0.24**	0.46***
	(0.027)	(0.091)	(0.061)	(0.031)	(0.105)	(0.072)
$\Delta y_{i,t-2}$				−0.01	0.51**	0.12
				(0.061)	(0.211)	(0.146)
$inv_{i,t-2}$				0.11***	0.18***	0.03
				(0.017)	(0.059)	(0.041)
$pub_{i,t-2}$				0.04	0.02	0.16**
				(0.033)	(0.113)	(0.078)
$\Delta y^{LR}_{i,t}$		4.84***	0.87***	7.25***	1.15**	
		(0.731)	(0.257)		(1.305)	(0.501)
$inv^{LR}_{i,t}$	−0.21***		0.08	−0.70*		0.06
	(0.044)		(0.051)	(0.382)		(0.076)
$pub^{LR}_{i,t}$	0.18**	0.95***		0.41*	0.89***	
	(0.077)	(0.262)		(0.231)	(0.319)	
N	240	240	240	224	224	224
Time dummies	yes	yes	yes	yes	yes	yes
Log likelihood		765.53			791.5	
AIC		−1235.1			−1237.8	

*Denote statistical significance at the 10% level **Denote statistical significance at the 5% level
***Denote statistical significance at the 1% level

sification of endogenous and exogenous variables used in the IV estimation setup to instrument the contemporaneous endogenous explanatory variables in the respective equations. An alternative to this approach is thus to start from an unrestricted VAR perspective, where each variable is treated as endogenous. The VAR then models each variable of the 3-equation system as a function of own lagged values and lags from the other variables of the system. A further advantage of the VAR methodology is that the dynamic properties of the system can be analyzed with the help of impulse–response functions. The latter approach may be seen as advancement compared to the 'dynamic multiplier' approach in standard DSEM modelling (see, e.g., Stein and Song 2002, for an overview).

Based on the FEM-3SLS estimator, we thus also estimate the model of $\Delta y_{i,t}$, $inv_{i,t}$ and $pub_{i,t}$ as VAR(1) and VAR(2) processes for panel data, where (1) and (2) indicate the maximum number of lags included. The results for the resulting PVAR models are shown in Table 8.14. As the table shows, both the PVAR(1) and PVAR(2) model get similar coefficient estimates, while the partial long-run elasticities of the PVAR(2) tend to be slightly higher compared to the PVAR(1) specification. In terms of minimizing the Akaike information criteria (AIC) the PVAR(2) is preferred over the single lag alternative.[21] We thus take this model to analyze the dynamic properties of the system and the potential two-way effects among the variables.

Impulse-response functions (IRF) describe the reaction of one variable to innovations in another variable of the system while holding all other shocks equal to zero (for details, see Lütkepohl 2005). In order to interpret the results, we compute orthogonalized IRFs which impose a certain causal ordering of the variables included in the VAR. Here we follow the standard in the literature and assume the following identification scheme (see, e.g., Marquez et al. 2009): Innovations in public investment affect contemporaneously private investment and output growth, but the reverse is not true; shocks to private investment affect contemporaneously output growth, but not the other way around. In this sense, the identified shocks are not subject to the reverse causality problem. The IRFs are shown in Fig. 8.21.

Figure 8.21 shows the responses of each variable to a one standard deviation shock in the remaining variables of the PVAR. We report the dynamic adjustment path of each variables up to 12 periods (years) together with 5% errors bands generated through Monte Carlo simulations with 500 repetitions.[22] Throughout this period, most of the dynamic adjustment processes have been taken place and the system returns to its long-run equilibrium. The general short-run adjustment dynamics of the system thus further supports the hypothesis of stationarity of the variables.

Both private and public investments react positively to shocks in output growth, where the effect levels out after about six to nine periods. On the contrary, a shock in private investment leads to a temporary negative reaction in Δy, while a shock in public investment does not show to have a significant impact on output growth. The reaction of public investment to a private investment shock turns out to be insignificant. However, private investment is positively affected by a shock in public capital investment. The latter effect of public capital is also found by Afonso and St. Aubyn (2009) for a sample of OECD countries.

In general, the predictions of the PVAR(2) are plausible in the light of economic theory. We find one-way causality from public to private investment. Both private and public investments show a positive reaction to shocks in output growth. However, there is no feedback causality from private and public investments to output growth. One likely explanation for the latter result is that the aggregate result is particularly driven by the economic evolution of the East German economy. Throughout the second half of the 1990s, the speed of growth and convergence for the East German economy towards the Western average considerably lost pace, while at the same time private and public investment rates were still relatively high compared to the Western states. Thus, the link between capital accumulation and output growth is found to be less tight for this sample period (see e.g. Alecke et al. 2010b).

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[21] We do not try higher-order lag lengths in order to keep the number of observations for estimation as large as possible.

[22] We use a Stata code kindly provided by Inessa Love to compute impulse–responses and variance decomposition in a Panel VAR framework.

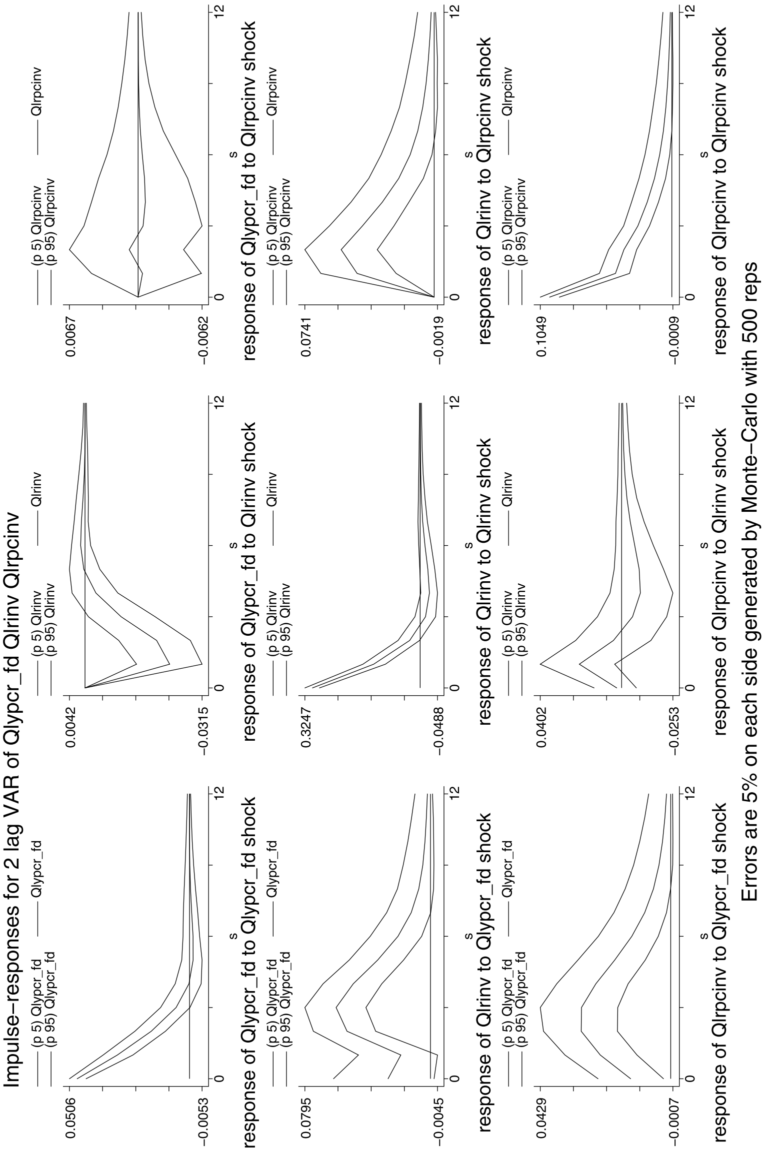

Fig. 8.21 Impulse–responses for PVAR(2) with $\Delta y_{i,t}$, $inv_{i,t}$ and $pub_{i,t}$. *Note*: With $\Delta y_{i,t} = Qlypcr\_fd$, $inv_{i,t} = Qlrinv$ and $pub_{i,t} = Qlrpcinv$

8.4.3 Interregional Spillovers from Public Capital and the Impact of Regional Transfers

We then use the baseline PVAR model to augment the scope of investigation to policy analysis. We run two types of exercises. First, we analyze the role of interregional spillovers from public capital installed in other regions. This issue was first addressed in Munnell and Cook (1990), arguing that the use of state level data misses important parts of the total spillover benefits relevant for the effective stock public capital and thus the policy making decision process. As Alvarez et al. (2006) points out, spatial spillovers from public capital may be explained as the result of network effects of public capital, where the stock of public capital is expected to affect production in other regions. This may particularly be relevant for building up transport infrastructure (e.g. roads, railways etc.).

According to Boarnet (1998) spillovers may not necessarily be positive. Negative spillovers from public capital may be present if the regional stock of public capital enhances the comparative advantages of a location relative to others so that public infrastructure investment in one location draws resources and thus production away from others. Different authors have contributed to the analysis of spillover effects from public capital. Pereira and Andraz (2008) find significant spatial spillover effects from public investments in highways for US state level data. The findings are supported by Pereira and Roca-Sagales (2003, 2006) and Marquez et al. (2010) for Spanish regions based on a general definition of public capital, while Alvarez et al. (2006) do not find any interregional spillover effect from public capital for Spanish provinces. Finally, using a different methodological approach based on bi-regional modelling, Marquez et al. (2009) show that both positive as well as negative interregional spillover effects may arise from public capital.

The typical approach to measure spillover effects from public capital is to introduce a spatially weighted variable capturing public capital investments in other regions as $\sum_{j\neq i,j=1}^{N} w_{ij} \times pub_{j,t}$, where w_{ij} is the ij-element of a spatial weighting matrix (W), which measures the degree of interregional dependence. As Alvarez et al. (2006) summarize common choices for the weighting scheme are i) a common border based definition with $w_{ij} = 1$ for adjacent regions and zero otherwise, ii) a distance related measure such as the inverse of the distance from other regions, iii) weights reflecting commercial relationships among regions and finally iv) equal weights as $1/(N-1)$.

We employ different weighting schemes to the analysis of interregional spillovers from public investments in transport and science infrastructure.[23] The IRF results for the distance based weighting scheme in ii) are reported in Figs. 8.22 and 8.23.[24] To keep the number of estimated parameters as small as possible we restrict the analysis to the PVAR(1) case. The impact of shocks for public capital investments in other German states on the remaining variables of the system are reported in

[23] Data is taken from DIW (2000) providing gross capital stock estimates for public infrastructure items at the state level until 2005.

[24] Further results for alternative weighting schemes can be obtained from the author upon request.

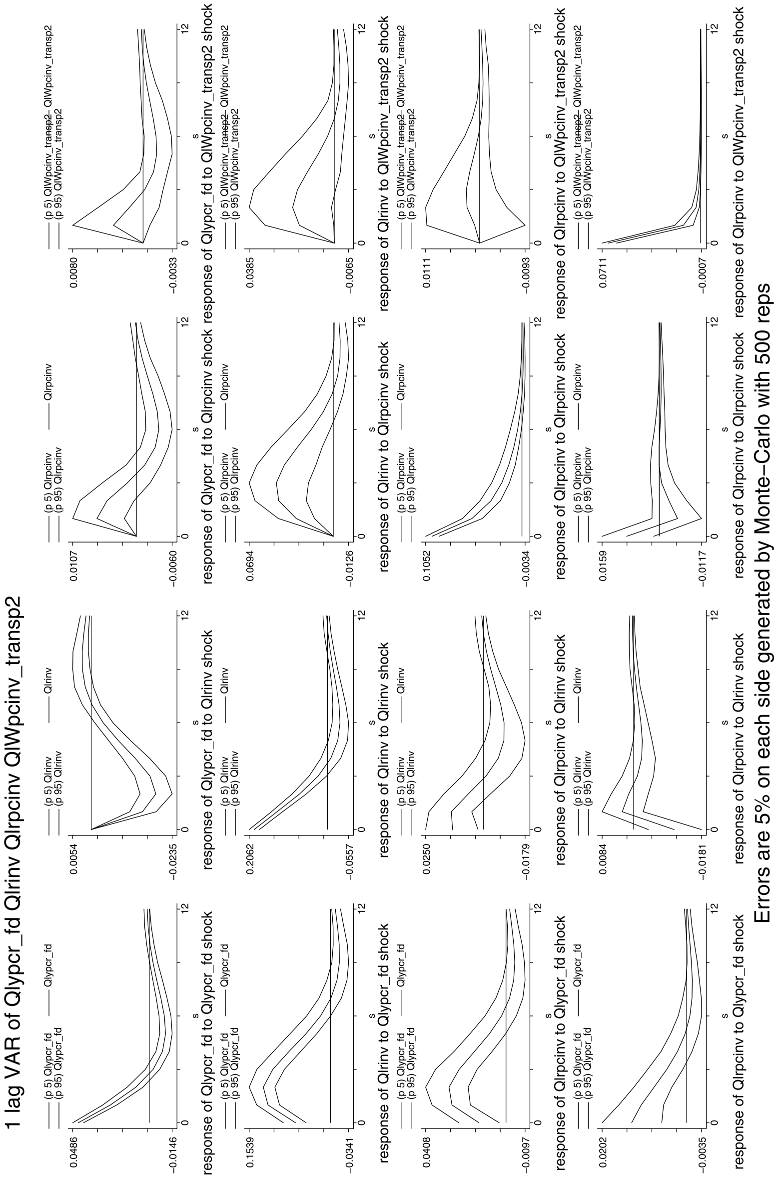

Fig. 8.22 Impulse-responses for PVAR(1) system with spillovers from transport infrastructure. *Note:* With $\Delta y_{i,t} = Qlypcr\_fd$, $inv_{i,t} = Qlrinv$ and $pub_{i,t} = Qlrpcinv$

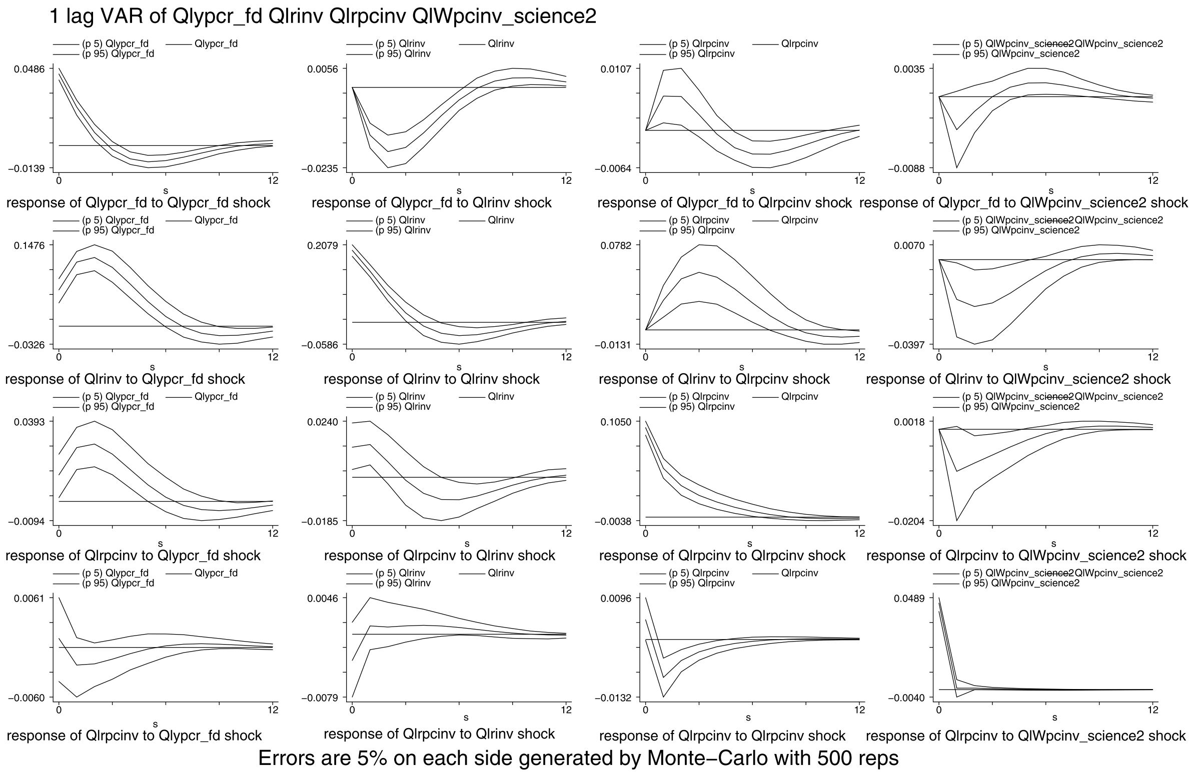

Fig. 8.23 Impulse–responses for PVAR(1) system with spillovers from science infrastructure. *Note*: With $\Delta y_{i,t} = Qlypcr\_fd$, $inv_{i,t} = Qlrinv$ and $pub_{i,t} = Qlrpcinv$

column IV of Figs. 8.22 and 8.23. For transport infrastructure (machinery & equipment, buildings & construction in transport and communication networks) we find positive but merely insignificant effects on $\Delta y_{i,t}$, $inv_{i,t}$ and $pub_{i,t}$. These results are qualitatively in line with recent results by Barabas et al. (2010), who find positive but mostly insignificant results for interregional spillover effects from transport infrastructure to output growth among German states. Bertenrath et al. (2006) as well as Uhde (2009) report mixed results, where the latter author even reports negative effects. One likely explanation for the absence of strong positive effects for German transport infrastructure investments is that the density of the transport network is high on average, so that gains from further investments turn out to be small.

Turning to the impact of spillovers from science infrastructure (machinery & equipment, buildings & construction for universities and public research facilities), the results in Fig. 8.23 hint at statistically negative effects from public capital investment installed in other regions to output growth and investment activity in the own region. This may enforce the argument raised by Boarnet (1998) that public capital enhances the comparative advantages of locations relative to others so that public infrastructure investment draws resources and thus production away from these locations. Especially for the case of science infrastructure, this may be relevant given the importance of human capital in the regions knowledge creation as an important determinant of economic development. Science infrastructure in turn may be seen as a necessary precondition for the region to attract human capital.

In a second type of exercise, we augment the PVAR by policy instruments operating as regional equalization payments. We focus on two of major policy schemes in the actual institutional setup of German regional policy: 1) the federal/interstate fiscal equalization transfer scheme (Länderfinanzausgleich, henceforth LFA), 2) the joint federal and state government program 'Improvement of Regional Economic Structures' (Gemeinschaftsaufgabe 'Verbesserung der regionalen Wirtschaftsstruktur', henceforth GRW).

Especially the LFA is a matter of constant debate at the political and academic level. A central question is whether those transfers associated with the LFA are effective in fostering growth in the relatively poor recipient regions and thus support the central goal of income convergence among German states. In the latter sense, equalization payments of the LFA are seen as an 'allocative' policy instrument, where positive macroeconomic effects are likewise associated with spillovers from public (infrastructure) investments as well as scale effects in the production of public goods (for a summary see, e.g., Kellermann 1998).[25]

In the recent literature, contrasting arguments can be found with respect to the likely macroeconomic effects of federal transfer payments such as the LFA. A typical argument against equalization transfers is that they may result in persistent

[25] The two layers of the LFA comprise a horizontal reallocation between different regional units of the same administrative level (states) as well as transfers stemming from vertical linkages between the federal government and the state level. The LFA targets the level of regional tax revenues, where equalization is achieved through a combination of horizontal and vertical transfer payments. Both elements serve as to subsidize low revenue states to fill the gap between a state's actual revenues relative to a population weighted average level of tax revenues across states.

'transfer dependencies', where poor net recipient regions have little incentives to boost their revenue base. However, LFA transfers can also been seen as a form of public capital which in turn may help to foster the productivity of private capital stock and thus also output growth. For the magnitude of this growth channel, the share of public investive spending items relative to total net transfers is important: The higher the share of investive (or supply side) spendings relative to total transfers, the stronger we expect the impulse of the LFA on the regional growth pattern to be.

Previous empirical contributions have shown mixed results: For Canada, Kaufman et al. (1997) find a significant positive influence of net transfer payments on the regional growth and convergence process of its provinces. Studies based on German data mainly reveal a negative relationship between LFA transfers and regional economic growth: Baretti (2001) uses data for 10 West German states between 1970 and 1997, Berthold et al. (2001) expand the approach to a panel of all 16 German states using a shorter observation period between 1991 and 1998. Both studies find a significant negative relationship between the elements of the LFA and regional growth in Germany. Alecke and Untiedt (2007) use a 'Barro'-type convergence equation to test for output effects using panel data for all 16 German states between 1994 and 2003. The results do not support any causal relationship between LFA payments and regional economic growth.

For LFA payments, the impulse–response functions from the PVAR(1) in Fig. 8.25 generally support the negative findings already reported in the empirical literature. That is, there a negative two-way effect running both from a shock in LFA payments to economic variables, as well as negative feedback effects. Regarding the impact of LFA transfers we get a significant negative reaction of private and public capital, while the effect on output growth is shown to be insignificant. A shock in output growth and public capital in turn leads to negative LFA payments. The output effect thereby basically mirrors the institutional setting of the LFA, while the two-way causality between public capital and LFA transfers gives support to the 'transfer dependency' argument, where the latter is typically faced by federal states with strong financial constraints due to a high burden of current spendings in total public spendings (see, e.g., Seitz 2004).

Another transfer scheme, the joint federal/state government programme Gemeinschaftsaufgabe 'Verbesserung der regionalen Wirtschaftsstruktur' (GRW), comprises two major components: First, the GRW operates as a regional investment support scheme for the private sector. Second, it provides public infrastructure to subsidized regions, where the infrastructure projects are closely related to the private sector business activity. There is a broad empirical literature analyzing the impact of various investment incentives on an economy's investment and growth path (a literature overview is given by Tondl 2001). So far, most evaluation studies of the GRW indicate a positive correlation between financial support and regional growth (for instance, Blien et al. 2003; SVR 2005; Eckey and Kosfeld 2005; Alecke and Untiedt 2007; Röhl and von Speicher 2009). However, only few studies try to spell out the transmission channels in a (structural) multiple equation model (see, e.g., Schalk and Untiedt 2000, for the latter approach).

The IRF results for the GRW are shown in Figs. 8.24 and 8.25, respectively. The impacts of shocks in regional GRW payments (per employee) to the remaining vari-

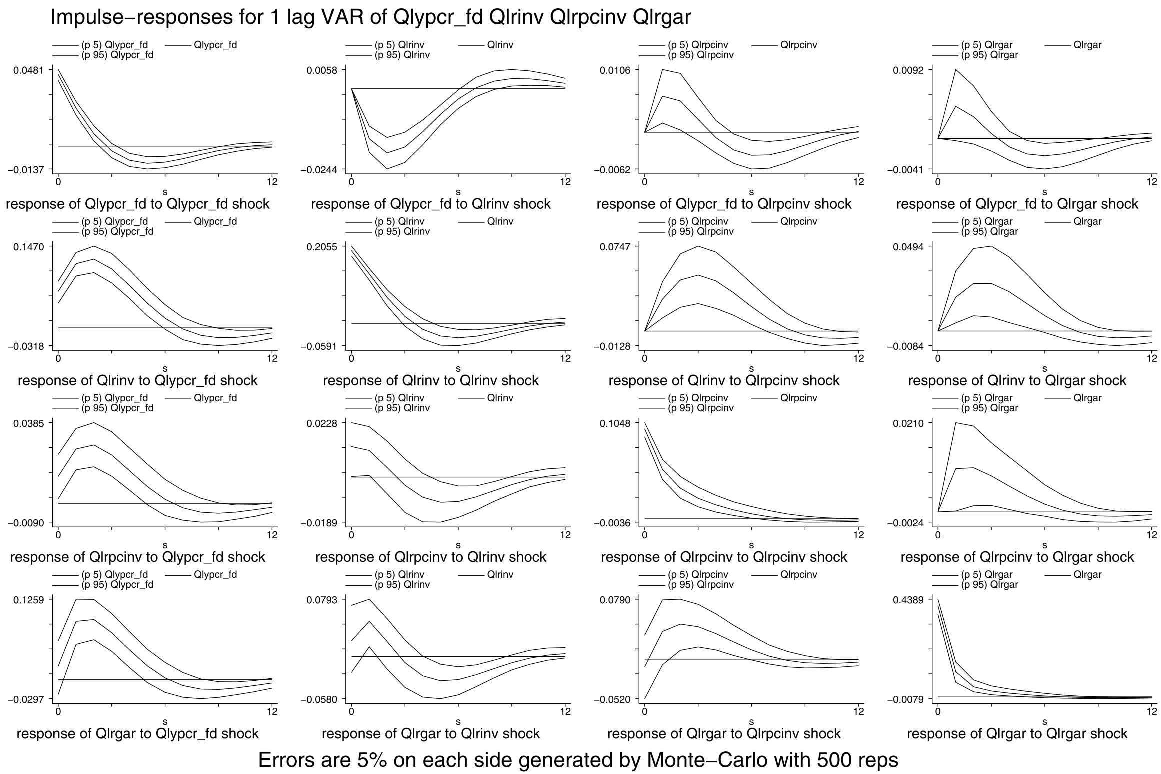

Fig. 8.24 Impulse–responses for PVAR(1) system with investment support grants (GRW). *Note*: With $\Delta y_{i,t} = Qlypcr\_fd$, $inv_{i,t} = Qlrinv$ and $pub_{i,t} = Qlrpcinv$

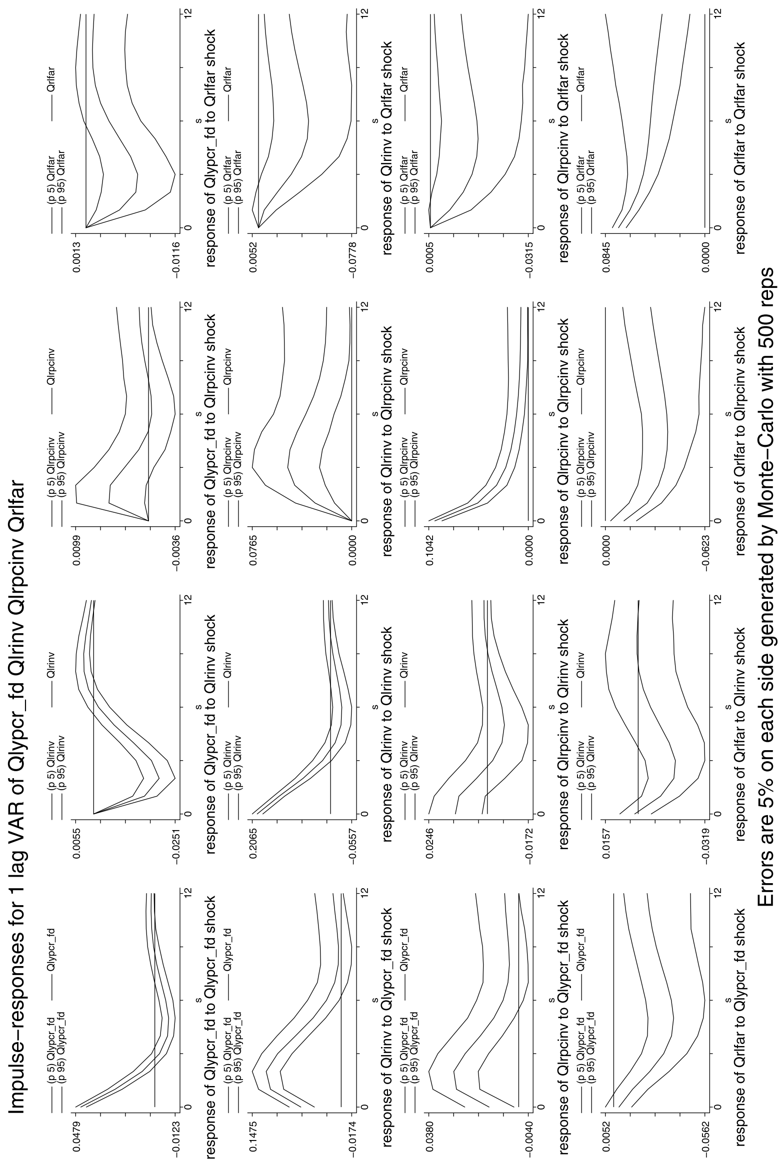

Fig. 8.25 Impulse-responses for PVAR(1) system with regional equalization payments (LFA). *Note*: With $\Delta y_{i,t} = Qlypcr\_fd$, $inv_{i,t} = Qlrinv$ and $pub_{i,t} = Qlrpcinv$

ables of the system are reported in column IV of Fig. 8.24. As the impulse–response functions show, the GRW has indeed a positive impact on public and private sector investment, although the effect already levels out after 3 periods (indicated by the intersection of the lower bound confidence interval with the zero line). However, this gives support to the effectiveness of the policy programme in terms of fostering private sector investment. Nevertheless, the graphs do not show any significant direct or indirect impact on output growth. That is, the GRW does not affect growth in total factor productivity directly. Moreover, as already seen in the baseline specification, there is also no indirect link running from an increase of investment to output growth. We finally observe significant positive feedback effects from shocks in $\Delta y_{i,t}$, $inv_{i,t}$ and $pub_{i,t}$ to regional GRW financial payments. This may indicate that a positive business climate in supported regions induces further demand for funding. Of course, these results only give a broad macro regional perspective and should be complemented up by other types on analysis, which are able to more carefully account for results at a more disaggregate regional scale.

8.5 Conclusion

Despite is potential use for efficient structural modelling, simultaneous equation estimation with panel data is still seldom applied in economics and regional science. This is particular true for time-dynamic processes. In this chapter we have taken up this point, dealing with two distinct research questions: First, we wanted to gain more insights regarding the small sample properties of different estimators. Although efficiency of full information approaches for the estimation of a system of equations is well known in large sample settings, the researcher is often left without device for finite samples. We thus provide further finite sample evidence for dynamic panel data models in multiple equation settings. We especially focus on two-sided small (N, T)-samples. Using a broad set of Monte Carlo simulation designs, we test the empirical performance of different multiple equation extensions for the standard FEM, its bias corrected form, as well as familiar IV and GMM style estimators, which have recently been proposed in the literature.

For the parameter settings employed in this Monte Carlo simulation exercise, our results show that simple estimators are also among the best: The FEM estimator using 2SLS/3SLS with valid exogenous instruments ranks best in terms of bias and also shows to have a good performance regarding the relative efficiency of the estimators. Note that we evaluate all regression parameters, not only regarding the autoregressive parameter in the dynamic specification. This result particularly holds for data settings, where the unobserved fixed effects make up a dominant part of the overall error term. For constellations with a high persistence in the autoregressive parameter of the endogenous variables as well as a small time dimension, e.g. $T = 5$, the LEV-SGMM estimator performs best. This estimator in general also ranks best in terms of efficiency (rmse). While the latter two estimators may thus be seen as a good choice for empirical applications, when right hand side endogeneity and simultaneity matters, GMM based estimation techniques in first differences, which are still a common tool in dynamic panel data setups, perform generally rather weak. To some extent, this also affects the performance of Blundell–Bond type system GMM estimators. These results can also be extended to the case of heteroscedastic errors.

The chapter then applies different dynamic simultaneous equation specification to a small-scale regional economic model for German states. Using a 3-equation approach for output growth, private and public capital investment, the model is able to identify the two-way effects among capital inputs and output growth. Augmenting this baseline model by variables to measure interregional spillover effects from public capital as well as transfer payments from regional equalization schemes, allows us to use to model for policy analysis. Here the results show that we find positive but insignificant effects from interregional spillovers in transport infrastructure, while spillovers from science infrastructure are shown to be even negative. The latter result is likely to originate from specific locational advantages of science infrastructure, which allows regions to poach production factors from their neighborhood. For regional equalization transfers we find mixed results, depending on the specific policy programme. While the German private sector investment promotion scheme (GRW) is found to have an positive impact on private and public investment, negative effects were found for equalization transfers at the level of the public sector (LFA).

Future research effort should more carefully account for the following aspects: From a methodological point of view it has to be further investigated whether standard statistical inference is valid for the evaluation of the different estimators in the two-sided small panel setting or whether bootstrapped standard errors should be seen as a promising alternative (see, e.g., Galiani and Gonzalez-Rocha 2002). For empirical application, full information estimation of small economic systems seems promising in order to properly control for endogeneity and simultaneity. Here, future attention should be paid to combine theoretical approaches (such as the dynamic stochastic general equilibrium approach, DSGE) with the power of dynamic panel econometric modelling and testing as recently proposed in the DSGE-VAR framework (see, e.g., Rickman 2010, for an overview). Another important step from a regional scientist perspective is to open up these models for a thorough analysis of spatial dependence, a topic which has been raised here only indirectly in the analysis of interregional spillovers.

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Chapter 9
Speed Up or Slow Down? The Effects of Capital Investment Grants on German Regional Growth

9.1 Introduction

In this chapter, we analyze the quantitative impacts of the regional policy scheme 'Joint Task for the Improvement of Regional Economic Structures' (in German, *Gemeinschaftsaufgabe "Verbesserung der regionalen Wirtschaftsstruktur"*, henceforth GRW) on labor productivity growth for a cross-section of 225 German labor markets between 1994 and 2006. The GRW is the key instrument of the German federal government and the states (the so-called 'Bundesländer') to foster investments in lagging regions with weak economic structures. Besides its redistributive effect of balancing out differences in the standards of living among German regions, the scheme is also intended to contribute to allocative efficiency. That is, by fostering economic performance in targeted regions, it shall ultimately contribute to German aggregate economic growth. From a theoretical perspective, the latter assumption holds in a perfectly neoclassical world. Here, due to decreasing marginal returns of capital, poor regions with a higher initial gap towards steady-state income grow faster relative to rich regions which are near their (identical) steady-state levels.

Given this potential 'double payoff' out of GRW spendings in terms of achieving two major social goals with a single instrument, it has attracted considerable interest in the empirical literature since its start in the late 1960s. The allocative motivation of the GRW is especially subject to criticism. Opponents question the predictions of (unconditional) convergence given the existence of increasing returns to scale, e.g. through agglomeration effects. Motivated by recent contributions in the fields of new growth theory and new economic geography, it is argued that from an allocative point of view the support of strong rather than weak regions would be in order.

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Jointly with Björn Alecke and Gerhard Untiedt. Björn Alecke, Gesellschaft für Finanz- und Regionalanalysen (GEFRA), e-mail: Alecke@gefra-muenster.de; Gerhard Untiedt, GEFRA & Technical University Clausthal, e-mail: Untiedt@gefra-muenster.de.

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Given these conflicting theoretical predictions, any economic impact analysis of the GRW needs to shift the focus to the empirical level. However, the picture is also not clear cut here: While some authors find positive economic effects, other scholars report insignificant or even negative correlations between GRW payments and regional growth for funded regions.[1] Moreover, recent research also extended the focus from a sole inspection of the direct effects of the GRW on supported regions to an augmented analysis including the likely role of spillover effects to neighboring regions.

The diversity of results found in the empirical literature can partly be explained by a plethora of different methodological approaches used for evaluation. Only few of them explicitly account for a thorough theoretical foundation, while the bulk of studies rather uses reduced-form models with weak identification strategies to estimate the causal impact of funding. Against this background this analysis attempts to specify an empirical model that explicitly refers to a growth-theoretical foundation. Additionally, we try to carefully account for new insights in the theory of spatial growth (regressions) and try to detect possible spillovers associated with regional policies, for instance, whether financial GRW support positively or negatively affects the growth path of neighbors. Negative spillovers may potentially arise from specific locational advantages of GRW support, which enable regions to poach factor inputs and thus production from their neighbors.

The remainder of the chapter is organized as follows: Sect. 9.2 presents some stylized facts of the institutional framework of the GRW. Additionally, it provides a literature review concerning the reported empirical impacts of the funding scheme on regional growth and convergence. This evidence serves as an empirical benchmark for our own estimation strategy to come in the next sections. Section 9.3 discusses the theoretical foundations of our empirical approach with a focus on neoclassical growth theory. Using this framework, the section then derives an empirical model to test for convergence in labor productivity among the German labor markets. We show how to properly incorporate GRW support as explanatory regressor, derive a testable null hypothesis in concordance with neoclassical growth theory and show how to interpret the estimation results. Section 9.4 presents the empirical results for our cross-section of 225 regions between 1994 and 2006. In Sect. 9.5, we augment the neoclassical but aspatial growth model by an explicit account for spatial dependence among the German regions—both with respect to productivity spillovers as endogenous variable as well as external effects originating from the set of covariates including the GRW. Section 9.6 finally concludes the chapter.

9.2 Institutional Setup and Literature Review

Since its introduction in the late 1960s, the GRW is operating as a coordinated action between the federal government and the states. For a time period of four years, they

[1] This result also mirrors conflicting empirical evidence for the success of regional policies at the European level (see, e.g., Ederveen et al. 2006; Dall'erba and Le Gallo 2008, for an overview).

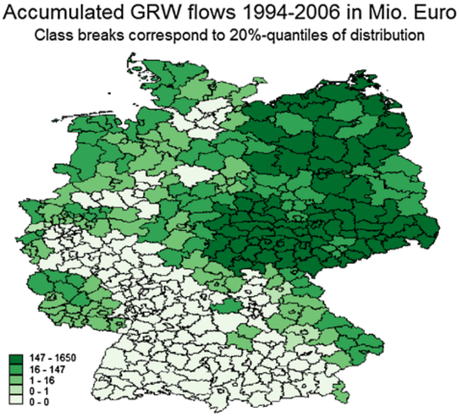

Fig. 9.1 Spatial distribution of GRW support among German labor markets. *Note*: For details about the data see Table 9.1

agree on a common general framework that contains the regulations for assistance—in particular the set of those regions which are eligible for public support. The two main instruments of the GRW are subsidies for investments of the private business sector in economically underdeveloped regions as well as the provision of local public infrastructure, which are closely related to private business activity.

In the course of German reunification the GRW scheme has been adapted on a one-to-one basis to the East German states. Between 1991 and 2009, the overall GRW budget amounted to 60.7bn. Euro with about two-third (39.3bn. Euro) assigned to private sector capital investment subsidies. The spatial distribution of cumulated financial flows to German regions is shown in Fig. 9.1. The figure shows that besides the East German states, which received about 85 percent of all GRW spendings, structural weak regions in North Germany, old-industrial centers in North Rhine-Westphalia, the Saarland and Rhineland-Palatinate received most parts of the GRW support. Besides it status as financially powerful funding scheme, the political importance of the GRW also stems from the fact that it acts as central coordination framework for most policies and programmes in Germany that intend to shape the regional development (such as the European Regional Development Fund (ERDF) and fiscal investment allowances in East Germany).

By now, there is a huge stock of empirical contributions aiming to analyze whether the GRW has achieved its political goals.[2] However, among these contributions there are only few approaches that are designed as a global impact analysis, addressing if and to what extent investment subsidies are causal for economic performance either at the firm or regional level. Instead, most evaluations conducted so far rather focus on the simple accounting principles such as execution and target control. One shortcoming of the latter approaches compared to a global impact is that they do not relate the observed outcome difference for supported regions over time (and/or relative to a comparison unit) to the notion of causality originating

[2]See, e.g., Bölting (1976), Franz and Schalk (1982, 1995), Klemmer (1986, 1995), Asmacher et al. (1987), Deitmer (1993), Lammers and Niebuhr (2002).

from the funding scheme. The latter approach would require that the strict 'with-without' evaluation principle has to be applied, which relates the observed outcome for a funded region to the counterfactual outcome situation, where everything else is unchanged except that the policy scheme is not implemented.

In general, impact analyses for the GRW could be conducted at the firm level or at the regional and macro-regional level. While the analysis at the firm level may be seen as a necessary condition for any policy effect to be at work, moving up the geographical level and looking at the region's performance, on the one hand, shifts the focus to the analysis of regional net effects for the funding scheme. This is particularly true if one assumes that there is a non-linear relationship between outcomes observed at the firm level and the regional scale. Non-linearities in turn may, for instance, stem from intra-regional spillover effects between funded and non-funded firms, which may augment or diminish the total regional effect. However, since the GRW programme is ultimately designed to foster regional growth, the analysis of regional net effects may still be justified from an evaluator's perspective. Also, an explicit advantage of studies at the regional and macro-regional level is that they are more likely to capture forward–backward linkages, second-round multipliers and feedback effects of the policy stimulus both for the region in focus as well as a system of interconnected regional units. That is, for example, while the funding of manufacturing firms is quite likely to have an impact on local suppliers and service providers, which then also affect the region's average per capita growth rate, such indirect effects are typically missed at any firm level analysis.

Since this analysis conducts a regional rather than firm level analysis, in the following review, we focus on related empirical contributions at the (macro-)regional level of aggregation. The international literature dealing with an empirical assessment of the effectiveness of capital investment support schemes dates back to the late 1980s and early 1990s. Here, at the international level, a variety of very similar studies have been published. Some examples are Luger (1984) for the US, Faini and Schiantarelli (1987) for Italy, Harris (1991) for Northern Ireland and Daly et al. (1993) for Canada, among others. Common to these studies is the simultaneous analysis of output and factor demand in small multiple-equation systems, focusing on the supply side of the economy. The approaches typically center around an output equation based on a production function approach as well as structural equations for factor demand in physical capital and labor, respectively. The advantage of estimating a structural model crucially driven by policy-induced changes in the user costs of capital is that the authors are able to identify both output and substitution effects between production factors, which are related to the investment support scheme.

The empirical results of this modelling approach are quite similar in the sense that they typically find a positive effect of investment promotion policies on output and investment. However, the empirically estimated effect on employment varies significantly among the different contributions. That is, while Daly et al. (1993) report negative employment effects as a result of a high elasticity of substitution between factor inputs, the results in Luger (1984) and Harris (1991) show rather moderate elasticities of substitution. In the analysis of Faini and Schiantarelli (1987), the output effect is even found to outweigh the substitution effect between factor demands for a policy-induced change in relative factor prices. This result is also confirmed by Schalk and Untiedt (2000), who were among the first to adapt the empirical method of analysis to the German case for a sample of 327 West German districts between 1978 and 1989. Subsequently, further empirical evidence was reported. Focusing on the East German economy, Blien et al. (2003) use a model with variable selection motivated by different streams of regional science to estimate the employment effect of GRW support. For the sample period 1993–1999, the authors find that GRW spendings have a significantly positive effect on the regional evolution of employment for East German districts.

An empirical contribution closely related to the design of our empirical analysis is the approach taken by the German Council of Economic Advisors (SVR 2005). Based on a conditional convergence equation, the SVR (2005) uses data for East German labor market regions between 1991 and 2001 and finds a significant positive effect of GRW support on productivity growth. Also, in a prior work to this study, Alecke and Untiedt (2007) find positive effects of GRW support when using a cross-sectional convergence equation for German labor markets between 1994 and 2003. Finally, Röhl and von Speicher (2009) use a rather a-theoretical estimation approach for a panel data set of 113 East German districts between 1996 and 2006. In their paper, different outcome variables are used as dependent variables including aggregate labor productivity and GVA in the manufacturing sector, respectively. They are regressed on a time trend, a set of dummy variables for regional settlement types, and lagged GRW payments. Both for aggregate as well as sectorally disaggregated model specifications the authors find significantly positive policy effects. Röhl and von Speicher (2009) also show that their results likewise hold for employment growth.

Even if some of the recent empirical contributions use a theoretically founded neoclassical convergence approach, one nevertheless has to carefully design the study regarding the inclusion of the policy variable. In this sense, most of the above discussed empirical approaches rest on specifications with an un- or misspecified functional form, which makes it extremely hard to interpret the obtained empirical results in light of economic theory. To take an example, even if the model is based on a neoclassical convergence equation of the 'Barro'-type form such as in SVR (2005), the ad-hoc inclusion of a policy variable like investment grants as right hand side regressor would imply that the null hypothesis being tested is whether the GRW policy has any impact on the regional long-run technology level, which in turn determines regional differences in long-run steady-state income. However, testing for its long-run steady-state implications clearly conflicts with the neoclassical growth model as theoretical basis of analysis, since the latter framework assumes that investment subsidies may only have a transitory impact on regional growth until long-run steady-steady is reached. We come back to this point in more detail when describing the theoretical predictions of the neoclassical growth model in Sect. 9.5.

Recent contributions dealing with the spatial effects of the GRW and similar funding schemes have shown that disregarding these effects may additionally lead to a bias in the overall assessment of the empirical effects. In a first empirical study, which explicitly controls for spatial effects, Eckey and Kosfeld (2005) use a cross-section of German labor markets for the year 2001 in order to identify direct and spatially related indirect effects of the GRW investment subsidies on per capita GDP. To measure the latter effect, the authors use a spatially augmented regression approach that incorporates spatial lags of the endogenous and exogenous variables as right-hand-side regressors. The main message from the analysis is that, although the authors find a positive direct effect for supported regions, they also reveal negative indirect effects, which entirely cancel the positive effect. However, for both effects the authors only get limited statistical support. Negative indirect effects of private sector investment grants are also reported in De Castris and Pellegrini (2005) for Italian regions. Both contributions hint to the likely importance of spatial effects in the analysis of regional policy schemes. We take up this point at latter stages of our empirical modelling strategy.

9.3 Theoretical Foundation and Empirical Specification

9.3.1 The Neoclassical Growth Model and Income Convergence

Besides the structural approach in Schalk and Untiedt (2000), most studies quantifying the empirical effects of the GRW rely on estimating a single equation reduced-form model. Typically they all start from a regression equation, in which the outcome variable of interest (such as growth in per capita GDP, labor productivity, or regional employment) is regressed on one or more policy variables such as GRW volumes in absolute terms or as a share of GDP or in relation to the population size, respectively. In order to be able to isolate the policy effect, a set of covariates is included in the regression which comprises variables that are necessary to control for economic determinants of the outcome variable besides the policy effect so that no omitted variable bias may apply. However, despite its importance, in empirical practice, the set of control variables is typically included in an ad-hoc and incomplete fashion, ignoring a thorough theoretically guided variable selection. A related criticism applies to the specification of the functional form of the empirical model which is seldom well-grounded on a special economic theory but simply assumes a linear relationship among the outcome variable on the one side and the policy and control variables on the other side of the equation.

In an attempt to account for these shortcomings, in this analysis we extend the empirical approach used in Alecke and Untiedt (2007) aiming for a growth theoretical foundation of the chosen empirical specification. Deriving an empirically testable model from growth theory has mainly two advantages. First, it allows us to compare the estimated model coefficients with the theoretically expected structural parameters. Second, it may guide variable selection. Based on theoretical as well as statistical arguments, we also put a special emphasis on controlling for spatial dependencies among the German labor markets. As Eckey and Kosfeld (2005) have shown, the inclusion of indirect spatial effects is an important part in conducting an impact analysis of investment support by the GRW scheme. From a statistical perspective, it additionally may help to avoid misspecifications regarding the models error term, which may result in biased and/or inefficient estimation results of aspatial empirical models.

Our model specification starts from neoclassical growth theory, which is a well-suited vehicle for the analysis of income convergence and the role of investment incentives. The main motivation for using the concept of convergence as a workhorse model is that it allows us to control for different initial income levels in the analysis of growth determinants. Initial income thereby serves as a proxy for the region's initial capital endowment (typically in units of efficient labor) and is expected to be negatively correlated with the growth rate of the regional economy, given decreasing marginal returns to capital. The fundamental ingredient of convergence analysis is then the idea of a transitory income path common to all regions, which exhibits declining growth rates towards the path to the steady-state income. Or in other words, initially 'poor' regions are expected to grow faster the more remote they are with respect to steady-state income. Besides the crucial assumption of the neoclassical growth model that i) the production factors capital and labor each have diminishing marginal products, the model predictions further depend on ii) an exogenous level of technology, and iii) constant returns to scale for the production factors capital and labor in the production function (see, e.g., Tondl 2001, for details).

Since the first assumption implies that the marginal productivity of capital is a negative function with respect to the accumulated capital stock, regions with lower stocks per capita will grow faster.[3] Assumptions i) to iii) together implies that regions will converge to a common steady-state income level, meaning that convergence is 'unconditional'. The only reason why regions show differences in their per capita income growth rate is the initially heterogeneous endowment with capital. In the long run, only a rise in the exogenously determined technology level leads to changes in the steady-state income. Relaxing the strong assumption of homogeneity in the long-run technology level leads to a different prediction known as 'conditional' convergence. Here regions face identical growth rates in steady-state. Nevertheless, their income levels may differ. Differences in the technology level are thereby typically treated as 'catch all' parameter for all kind of potential driving factors of regional long-run income such as the regional knowledge stock, human capital, and public infrastructure. Finally, spatial linkages such as the ability to absorb knowledge from other regions also potentially drive the region's long-run income level. We give an account of the concept of spatial convergence in Sect. 9.5.

Both for 'conditional' as well as 'unconditional' convergence, the implications from changes in the private investment rate, as intermediate goal of investment subsidies, are then easily accessible in the neoclassical framework. The model basically predicts that a permanent increase in the economy's investment rate leads to a temporary increase in the economic growth rates with a permanent shift of the economy's steady-state income level. The basic intuition behind the model's transmission mechanism can be easily shown by means of graphical presentation (for details

[3] In the literature, this concept of convergence is also known as β-convergence. The latter is a necessary (although not sufficient) condition for the reduction of income disparities, known as σ-convergence.

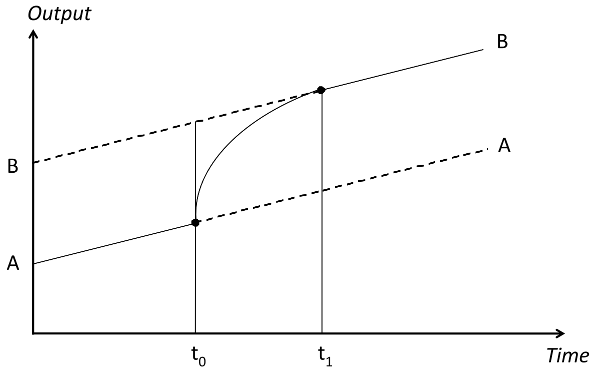

Fig. 9.2 Effect of a permanent increase in the physical investment rate

see, e.g., Tondl 2001; Favero 2001). Figure 9.2 shows a representative economy along its long-run (or steady-state) growth path AA as a function of exogenously determined technical progress.

In time period t_0, the investment rate is permanently increased (e.g., via an investment subsidy scheme). As the figure shows, this leads to a temporary increase in the economy's growth rate between time period t_0 and t_1. However, the more the economy converges towards its new path BB in t_1, this effect vanishes. Nevertheless, there is a permanent level effect resulting in a higher steady-state growth path BB with a higher output (productivity) level as a result of increased investment activity. For economic policy, it is important that this level effect is only permanent if the increase in the investment rate is long lasting. Otherwise, the economy would return to the long run path AA. In the next section, we show how to translate this effect into an empirically testable form.

9.3.2 Empirical Specification of the Convergence Equation

In seminal papers, Barro and Sala-i-Martin (1991, 1992) have initiated a bulk of empirically oriented studies, analyzing income convergence among groups of nations as well as regions within a national economy. The starting point for empirical estimation in a cross-sectional context is a convergence model derived from neoclassical growth theory as

$$(1/T)\log[y_{iT}/y_{i0}] = g + \frac{(1-e^{-\beta T})}{T}\log[y_i^*/y_{i0}] + u_{i0,T}, \tag{9.1}$$

where i is the cross-sectional dimension as $i = 1, \ldots, N$, T is the time dimension for which the change in the output variable y is measured, y_{i0} and y_i^* denote initial and steady-state levels of the outcome variable. u is the model's error term with standard normality assumptions, g denotes the constant rate of technology growth and β is the convergence rate, which can be interpreted as the region's annual speed of convergence (measured in percentage terms). Since neither the steady-state income level nor its growth are observable, a convenient way to estimate (9.1) in its unconditional form is to introduce a common intercept a_0 that captures the steady-state income level for the set of regions as

$$a_0 = g + [(1 - e^{-\beta T})/T] \times [\log(y_i^*)], \tag{9.2}$$

so that (9.1) reduces to

$$(1/T)\log[y_{iT}/y_{i0}] = a_0 - b \times \log(y_{i0}) + u_{i0,T}, \tag{9.3}$$

where β can be recovered from the regression coefficient b as $b = (1 - e^{-\beta T})/T$. In analyzing income convergence, special attention is devoted to the interpretation of the coefficient b. If $b < 0$, convergence forces are at work, meaning that initially poorer regions grow faster than richer ones. However, $b < 0$ is not a sufficient condition for unconditional convergence to occur. The latter in fact would require that the empirical regression shows a good fit with respect to the data analyzed; especially the residual term should not capture the effects from any omitted variable. Moreover, the convergence rate β should be in accordance with its theoretically expected value, where β can be derived as $\beta = (1 - \alpha)(g + n + \delta)$, and α is the output elasticity of capital, n and δ are population growth and capital depreciation rate respectively (see, e.g., Tondl 2001, for details). In the empirical literature a 'rule-of-thumb' for $\beta \approx 0.02$–0.03 has been established, which holds for different sample settings involving both national and regional data (see, e.g., Barro and Sala-i-Martin 1991, 1992, 2003).

Estimating conditional convergence relaxes the assumption of a common intercept a_0 as proxy for the steady-state income level of regions under study. As argued in the above section, there are different potential driving forces of the region's technology level such as the regional knowledge and human capital stock or the endowment with public capital. One straightforward way to control for region-specific steady-state income levels would imply to include N individual effects a_i as

$$(1/T)\log[y_{iT}/y_{i0}] = a_i - b \times \log(y_{i0}) + u_{i0,T}. \tag{9.4}$$

However, in a cross-section setup, estimating (9.4) is not feasible since it requires estimating N fixed effects for the N regions involved, which implies that the number of regression coefficients ((N + 1) = N individual effect plus the convergence parameter b) exceeds the number of observations N. An approach to circumvent this problem for the estimation of conditional convergence equations is to substitute the individual effects by k coefficients from a variable vector X that controls for differences in the steady-state levels as[4]

$$a_i = a + c_1 \log(x_{1,i}) + c_2 \log(x_{2,i}) + \cdots + c_j \log(x_{j,i}) + \cdots + c_k \log(x_{k,i}). \tag{9.5}$$

Substituting (9.5) into (9.4) leads to a conditional convergence equation, which can be estimated as

$$(1/T)\log[y_{iT}/y_{i0}] = a - b \times \log(y_{i0}) + \sum_{l=1}^{k} c_j \log(x_{l,i}) + u_{i0,T}. \tag{9.6}$$

[4]Using logarithmic values for each variable x, which allows us to directly interpret the obtained regression coefficients as elasticities.

As Tondl (2001) points out, conditional convergence analysis tests for convergence to different steady-state income levels and not a common one as in (9.3). Thus, any estimation including variables $x_1, \ldots, x_k$, even if they are only dummy variables for each regional economy, investigates convergence to different steady-state income levels. As argued above, we should thereby carefully use theoretical considerations in guiding variable selection for $\sum_{i=1}^{N} c_i x_i$. Besides factors directly related to the neoclassical growth concept, further regressors motivated by new growth theory, new economic geography, and/or more traditional strands of regional economics have been suggested in the literature. These typically include:

- the regional knowledge intensity measured in terms of patents and high-tech sectors,
- the degree of international openness and external input–output relations,
- the regional stock of human capital,
- the region's market potential, proxied by the market size in surrounding areas,
- geographical advantages of the regions
- localization and urbanization effects.

Besides these long-run control factors, policy variables can be included in the regression framework. Typically this has been done in the following ad-hoc fashion

$$(1/T)\log[y_{iT}/y_{i0}] = a_0 - b \times \log(y_{i0}) + \sum_{j=1}^{k} c_j x_{j,i} + \gamma s_i + u_{i0,T}, \qquad (9.7)$$

where the coefficient γ measures the impact of policy intervention s_i on growth. However, adding s_i as further regressor to $\sum_{i=1}^{N} c_i x_i$ implies that the researcher tests for the null hypothesis of the policy driving differences in the steady-state income level for the sample of regions in focus. However, this is not an appropriate model design for the analysis of investment incentive schemes, which is only expected to affect the transitory growth dynamics in convergence to long-run steady-state income level, but leaving differences in the long-run steady-state income level unaffected. As explained in the following, we thus modify (9.7) to properly account for the predictions of growth theory when designing an empirical test for GRW policy effectiveness.

To measure the policy impact from GRW, two alternative variable definitions are generally possible. First, regions eligible for receiving GRW subsidies can be identified by a binary dummy variable, which takes a value of one if the region has received subsidies for the period of analysis and zero otherwise. Second, total GRW spendings normalized by size or performance indicators of the region (such as population, total employment or regional GDP) can be used, which results in a measure for the funding intensity of the policy scheme. Private and public capital investment subsidies are then expected to influence the speed of convergence of the regional economy towards its steady-state. We operationalize this transmission channel by including an interaction term defined as the policy variable times initial income as $s_i \times y_{i0}$. As Bambor et al. (2005) point out, in order to adequately measure the marginal effect of funding conditional on these two exogenous variables, s_i and y_{i0} have to be included in the regression framework:

$$(1/T)\log[y_{iT}/y_{i0}] = a - b \times \log(y_{i0}) + \sum_{j=1}^{k} c_j x_{j,i} + \gamma s_i + \xi[\log(y_{i0}) \times s_i] + u_{i0,T}, \quad (9.8)$$

where $s_i = [D_{GRW}, \log(GRWQ)]$ with D_{GRW} as binary dummy for GRW regions and $\log(GRWQ)$ is a proxy for funding intensity. The use of the interaction term in the convergence equation can be motivated as follows. As shown, the convergence rate β is determined by the output elasticity of capital, as well as population growth and capital depreciation rate, respectively. This fixed relationship, however, only holds for a closed economy. For regional analysis, the latter assumption does not seem plausible since we can expect a high mobility of capital among interrelated regional units.

The introduction of (incomplete) capital mobility in the neoclassical growth model framework can then be done conditional on the initial income level, so that the value of the convergence rate β additionally captures the effect of capital mobility. To be more precise, the convergence rate β can now be formulated as $\beta = (1-\alpha)(g+n+\delta+\omega)$, where ω reflects the elasticity of external capital supply. Thus, as long as ω is non-zero, taking capital mobility into account, it obviously increases β. As Schalk and Untiedt (1996) point out, the basic assumption for this transmission channel to work is that the external capital influx is determined by regional differences in the marginal return of capital. However, it is precisely the goal of investment subsidies by the GRW to reduce the user cost of capital and thus to affect regional differences in the marginal return of capital in favor of supported regions. Not accounting for this policy-induced change in the regional rate of return to physical investment in poor regions would result in a biased estimation of β. We expect that the regression coefficient for the interaction term ξ is negative, which implies that the speed of convergence for supported regions is enhanced. The total convergence rate can then be measured as $(b+\xi) = (1-e^{-\beta T})/T$.

The theoretically expected relationship between initial income and the GRW policy effect induced by a permanent increase in the investment rate is shown graphically in Fig. 9.3. The negative coefficient ξ for the interaction term implies that, for each initial income level below the steady-state (y^*), funded regions show a

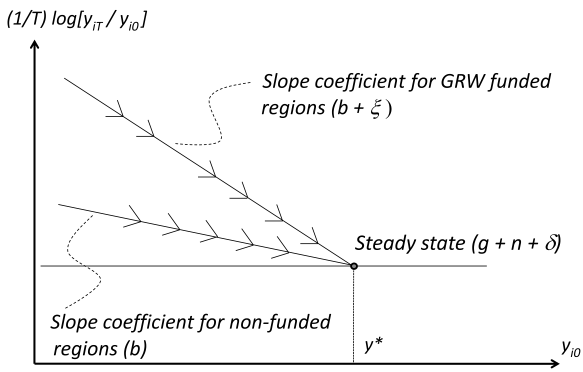

Fig. 9.3 GRW policy induced change in slope coefficient of convergence equation

higher speed of convergence in the growth/initial income-diagram relative to non-funded regions. The intersection of convergence curves for funded and non-funded regions marks the steady-state income level, where regions uniformly grow by $(g + n + \delta)$, driven by the constant rate of growth of technology (g), population growth (n), and the capital depreciation rate (δ). Equation (9.8) represents a special case of a more general empirical setup, which relaxes the assumption of homogeneous regression parameters between funded and non-funded regions in (9.8). This would lead to a fully interacted switching-regime model specification and would imply testing for significantly different long-run convergence clubs for the set of funded and non-funded regions. The model in (9.8) may thus be seen as a nested specification, which assumes statistical insignificance of interaction terms for $[s_i \times \sum_{i=1}^{N} c_i x_i]$.[5]

9.4 Data and Empirical Results

To estimate cross-section convergence equations as in (9.3) and (9.8) we use data on 225 German labor markets for the period 1994–2006. The year 1994 was chosen as a starting point to account for structural distortions in East Germany directly after reunification. Since geographical boundaries of German labor markets vary over time, we use the definition of labor markets valid just before the start of our sample period—dated back to the year 1993—in order to consistently track the GRW funding areas (see Hierschenauer 1994, for details). The dependent variable used throughout the analysis is growth in real labor productivity Δy_i, where Δ is the difference operator for logarithmic values of y according to $\Delta y = (1/T)(y_{iT} - y_{i0})$, i is the index for German labor markets according to $i = 1, \ldots, 225$ and T is the length of the time period, in our case $T = 13$.[6]

To measure the effect of GRW subsidies, we use both a dummy indicating the status of the region as either being supported over the sample period or not, as well as the intensity of GRW funding defined as total granted financial spendings in relation to the working age population in the region. We sum up both categories of GRW (private sector investment subsidies and business related public infrastructure). To account for differences in the economic structures of the 225 German labor markets, we use different control variables, which are listed in Table 9.1. Summary statistics of the variables are given in Table 9.2.

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[5]We also tested for significance of the remaining interaction terms in the full regime switching model. However, the obtained results did not provide strong empirical support for the latter. Moreover, the stability of the convergence parameter β was unaffected, so that we work with the nested model specification in the following.

[6]As alternative outcome variable, we also used per capita GDP. Since the results turned out to be very similar, the latter results are not reported here but can be obtained from the authors upon request. The main difference between labor productivity and per capita GDP is the consideration of the labor participation or unemployment rate, which is typically not the focus of empirical growth analysis.

Table 9.1 Variable descriptions for the regional productivity growth model

Variable	Definition	Theoretical concept	Mnemonic
Initial level of labor productivity	GDP per total employment in 1994	Capital accumulation per unit of efficient labor	log(*Y94*)
Physical investment intensity	Physical investments in manufacturing sector per total employment (av. 1994–2006)	Capital accumulation per unit of efficient labor	log(*S*)
Capital accumulation per unit of efficient labor	Employment growth	Change in total employment 1994–2006 (plus 0.04 for exogenous growth in technical progress and depreciation rate)	log(*EWT*)
Skill level of labor force	Employment share with at least one level of vocational qualification (av. 1994–2006)	Human capital	log(*HK*)
Patent intensity	Patents per labor force (av. 1995–2005)	Innovation & Competition	log(*PAT*)
Employment share of manufacturing sectors	Share of employment in manufacturing sectors in total employment (av. 1998–2006)	Innovation & Competition	log(*IND*)
Employment share of high-tech sectors	Share of employment in technology intensive sectors according to ISI/NIW classification per total employment (av. 1998–2006)	Innovation & Competition	log(*TECH*)
International openness	Share of foreign turnover per total turnover for manufacturing sector (av. 1994–2006)	Innovation & Competition	log(*AUM*)

(*continued on the next page*)

Table 9.1 (Continued)

Variable	Definition	Theoretical concept	Mnemonic
Sectoral specialization	Sum of squared deviations in employment shares for each NACE3 sector between region and national average in 1998	Localization advantages	$\log(SPZG)$
External economies of scale	Employment in sectors with high Ellison–Glaeser index (> 0.005) relative to total employment in the region	Localization advantages	$\log(EGH)$
Market potential	Sum of GDP in own region plus GDP of neighboring regions, weighted by inverted distance between regions	Settlement structure & Locational advantages	$\log(MPOT9)$
Transport accessibility	Average travel time in minutes for road and air traffic to all 41 European agglomeration areas in 1998 (BBSR transport network model)	Settlement structure & Locational advantages	$\log(ERBK)$
Population density	Population per km^2	Settlement structure & Locational advantages	$\log(BV)$
Indicator for GRW supported regions	Binary dummy: If region has received GRW funds = 1, otherwise 0	GRW promotion scheme	D_{GRW}
Total GRW volume	Sum of GRW funds per labor force in 1994–2006 (zeros are replaced by small values before log-linearization)	GRW promotion scheme	$\log(GRWQ)$

Source of Data: Federal Institute for Research on Building, Urban Affairs and Spatial Development (BBSR 2009), Federal Employment Agency (2009), VGR der Länder (VGRdL 2009), own calculations

Table 9.2 Descriptive statistics for variables

Variable	Mean	Max	Min	St. dev.
Labor productivity growth	0.021	0.055	−0.003	0.009
Initial productivity level in 1994	42915	61906	27973	7452
Employment growth	0.002	0.023	−0.028	0.008
Physical investment intensity	0.058	1.233	0.016	0.092
Vocational training	0.802	0.909	0.662	0.058
Employment share in manufacturing	0.268	0.719	0.068	0.110
International openness	0.288	0.617	0.037	0.109
Employment share in high-tech sectors	14.05	58.26	3.75	7.40
Patent intensity	609.8	2754.2	40.6	462.2
Sectoral specialization	0.897	1.556	0.499	0.194
External economics of scale	146.5	2935.7	34.3	259.6
Market potential	275.5	386.3	199.7	31.1
Geographical accessibility	11746	42770	2414	7388
Population density	252.9	3552.5	40.5	349.6
GRW intensity	69.9	1084.9	0.001	139.2

Source: See Table 9.1

Fig. 9.4 Regression results for unconditional convergence among German labor markets

We start with the regression equation for unconditional convergence among the 225 German labor markets according to (9.3). As Fig. 9.4 shows, the graphical presentation of the regression results for b indeed shows a significantly negative correlation between initial labor productivity in 1994 and productivity growth for the period 1994–2006. The regression line in Fig. 9.4 has a slope coefficient of $b = -0.036$ (t-statistic $= 15.5$). Recovering the convergence rate β from the fitted model, shows an annual speed of convergence of roughly 4.7 percent, which is slightly above the average convergence speed of 1–3 percent reported in the empirical literature for Germany. A convergence speed of $\beta = 4.7$ percent implies a half-life H as time period to close half of the gap towards long-run steady-state productivity level with $e^{-\beta t} = 1/2$ as

$$H = \log(2)/\beta = 0.69/\beta \quad \text{for } \beta = 0.047 : H \approx 14.7, \tag{9.9}$$

which means that it takes about 15 years to close half of the gap to the common long-run labor productivity level. However, as Fig. 9.4 demonstrates, the empirical variance around the fitted regression line is rather high. The fit of the regression is $R^2 = 0.52$. Thus, only half of the variation in regional growth rates can be explained by initially different productivity levels.

In order to further investigate the convergence relationship, we move on to test for the validity of its conditional form according to (9.6) and (9.8). Results for different model specifications are shown in Table 9.3. Columns I and II thereby report specifications including the full set of control variables as listed in Table 9.1 including the two different indicators for GRW subsidies. In column I, we add the dummy D_{GRW} plus the interaction term; in column II, we include GRW funding intensity $\log(GRWQ)$ and the interaction term. In both specifications we find a significantly negative coefficient for the interaction term, indicating that the convergence speed increases due to GRW subsidies. For the dummy-variable approach in column I, we also test for the heterogeneity of the coefficient in the interaction terms between West and East German labor markets. The results show that the imposed restriction of slope-coefficient homogeneity between the two macro regions cannot be rejected on the basis of a Wald F-test. In columns III and IV, we exclude insignificant control variables, which lead to more parsimonious model specifications. The null hypothesis of validity of parameter restrictions in the parsimonious model cannot be rejected on the basis of a set of likelihood ratio tests (see Table 9.3).

Turning to the interpretation of the results with regard to the quantitative impact of GRW subsidies on regional labor productivity, columns III and IV in Table 9.3 show that convergence forces are still in order. However, the estimated coefficients for the initial level of labor productivity for non-funded regions are somewhat smaller than the coefficients found in the unconditional convergence equation, that is, in column III, we get a regression coefficient of $b = 0.026$ and in column IV, of $b = 0.032$. These parameter results imply a convergence rate β of 3.1 and 4.1 percent respectively. As Bambor et al. (2005) point out, the coefficient of the interaction term has to be interpreted conditional on the estimated coefficients for y_{i0} and s_i. In order to quantify the additional growth impulse of GRW support, we take the difference in the convergence rate between funded and non-funded regions as $\xi = (1 - e^{-\beta_{net} T})/T$, solve for β_{net} and then use the obtained coefficient to measure the difference in the speed of convergence conditional on the gap to steady-state income as:

$$\Delta_n y_i = \beta_n \times (y^* - y_{it}). \tag{9.10}$$

$\Delta_n y_i$ measures the marginal effect of GRW funding conditional on the region's gap at time period t to the long-run steady-state level y^* (in percentage points). To take an example, the estimated coefficient for the interaction term according to

Table 9.3 Conditional convergence estimation among German labor markets 1994–2006

Dep. var.: $(1/T)\log[y_{iT}/y_{i0}]$	I/OLS	II/OLS	III/OLS	IV/OLS
Initial labor productivity	-0.0257^{***}	-0.0324^{***}	-0.0233^{***}	-0.0315^{***}
$\log(Y94)$	(0.00267)	(0.0043)	(0.0066)	(0.0041)
Employment growth plus $(g+\delta)$	-0.0062^{***}	-0.0060^{***}	-0.0060^{***}	-0.0054^{***}
$\log(EWT)$	(0.0020)	(0.0010)	(0.0020)	(0.0019)
Investment intensity	0.0044^{***}	0.0044^{***}	0.0045^{***}	0.0048^{***}
$\log(S)$	(0.0012)	(0.0012)	(0.0011)	(0.0012)
Vocational training	0.0210^{*}	0.0178^{***}	0.0108	0.0115
$\log(HK)$	(0.0108)	(0.0110)	(0.0101)	(0.0105)
Share of manufacturing sector	0.0034^{***}	0.0037^{**}	0.0049^{***}	0.0048^{***}
$\log(IND)$	(0.0017)	(0.0015)	(0.0014)	(0.0014)
International openness	0.0015	0.0013		
$\log(AUM)$	(0.0011)	(0.0015)		
Share of high-tech industries	0.0013	0.0026^{*}	0.0036^{***}	0.0035^{***}
$\log(TECH)$	(0.0011)	(0.0015)	(0.0012)	(0.0012)
Patent intensity	0.0015^{*}	0.0008		
$\log(PAT)$	(0.0009)	(0.0009)		
Ellison–Glaeser index	0.0026	0.0016		
$\log(EGH)$	(0.0021)	(0.0021)		
Sectoral specialization	0.0005	0.0005		
$\log(SPZG)$	(0.0007)	(0.0007)		
Geographical accessibility	-0.0044	-0.0011		
$\log(ERBK)$	(0.0062)	(0.0061)		
Market potential	0.0009	0.0015		
$\log(MPOT)$	(0.0013)	(0.0013)		
Population density	-0.0088	-0.0060^{*}	-0.0100^{*}	-0.0067
$\log(BVD)$	(0.0054)	(0.0052)	(0.0053)	(0.0051)
Squared population density	0.0006	0.0003	0.0008^{*}	0.0005
$\log(BVD^2)$	(0.0004)	(0.0005)	(0.0005)	(0.0004)
Dummy for GRW regions	0.0671^{**}		0.0812^{***}	
D_{GRW}	(0.0308)		(0.0294)	
GRW intensity		0.0093^{***}		0.0099^{***}
$\log(GRWQ)$		(0.0030)		(0.0029)
Interaction term	-0.0181^{**}	-0.0025^{***}	-0.0222^{***}	-0.0027^{***}
$\log(Y94)\times s_i$	(0.0080)	(0.0008)	(0.0077)	(0.0008)
Adj. R^2	0.68	0.70	0.68	0.70
Wald test for interaction term $GRW_{West} = GRW_{East}$	$F = 0.03$ (0.85)			
LR-test for model I/II vs. III/IV			$\chi^2(6) = 5.01$ (0.54)	$\chi^2(6) = 4.66$ (0.58)

Source: Standard errors in brackets. In the specification of the interaction term s_i indicates, that depending upon the unconditionally included regressor as $s_i = [D_{GRW}, \log(GRWQ)]$ also the computation of the interaction term varies

*Denote statistical significance at the 10% level **Denote statistical significance at the 5% level

***Denote statistical significance at the 1% level

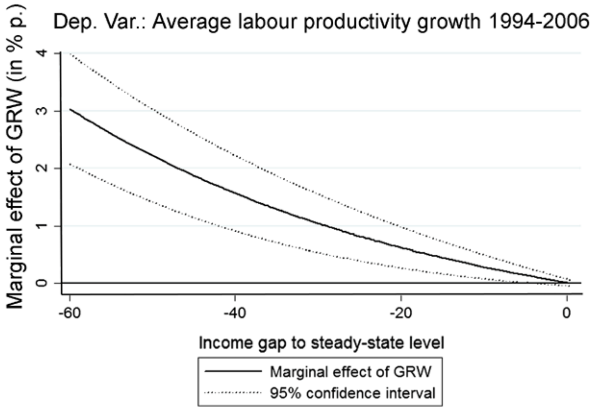

Fig. 9.5 Marginal effect of GRW subsidies relative to regional income gap

model specification in column III of Table 9.3 is $\xi = 0.022$. This implies that the total effect b increases in absolute terms as $|b| = (0.022 + 0.023) = 0.045$. The latter in turn can be interpreted as convergence rate for founded labor market regions as $\beta = 6.5$ percent. The difference in the speed of convergence between funded and non-funded regions after controlling for further growth determinants amounts to 3.8 percentage points. Using this convergence rate, we now can plot the distribution of the additional growth impulse of public support conditional on the observed empirical variance of labor productivity for funded labor market regions. This effect is shown graphically in Fig. 9.5.

The horizontal axis in Fig. 9.5 shows the income gap for funded labor market regions relative to their steady-state level.[7] The vertical axis plots the marginal effects of the GRW in percentage points. The displayed distribution of the marginal effects relative to the income gap in Fig. 9.5 can be interpreted as follows. Assuming that a funded labor market region has an actual income level of 50 percent of its long-run steady-state level, the specific growth impulse of the GRW investment subsidy increases the convergence rate of about 2.6 percentage points. This in turn translates to roughly a doubling of its speed of convergence taking that the average growth rate for the 10% lowest income percentile of German regions is around 2.5 percent. The 95-percent confidence interval in Fig. 9.5 also shows that the effect remains significant for most numerical values of the income gap. In line with our theoretical expectations, it is declining the closer the region is relative to its long-run steady-state income position.[8] Effectiveness of the funding scheme is thus the higher the further away the subsidized region is from its steady-state productivity level.

[7]For simplicity, we assume that funded labor markets converge to the same steady-state level. Here, we simulated different scenarios, either taking the 100 or 80 percent income percentile for non-funded West German regions as benchmark level. The latter assumes that even in the in long-run, German regions do not fully converge to a common income level, e.g., due to differences in the technological efficiency of regions (see, e.g., Schalk et al. 1995). We report results for the first scenario in Fig. 9.5, further results can be obtained upon request.

[8]For the computation of confidence intervals in interaction models see Bambor et al. (2005).

Also, for most of the other economic control variables in Table 9.3, we get empirical support in line with their growth-theoretic underpinnings. That is, as expected by the neoclassical framework, employment growth has a negative effect on labor productivity growth, while physical investments per employee translate into positive growth effects. Looking at the impact of the regional knowledge stock, the coefficient for the share of high-tech industries (measured as the relative employment share in total employment) is found to be statistically significant and of positive sign, while the effect of the patent intensity—although of the right sign—only turns out to be significant at the 10 percent level in the specification reported in column I. The share of manufacturing industries in the total composition of the regional economy similarly exhibits a positive correlation with labor productivity growth. The latter gives empirical support for the hypothesis of 'unbalanced growth' between manufacturing and service industries as postulated in Baumol (1967).

A further important variable to control for long-run differences in regions' steady-state productivity levels is the endowment of skilled employees. Here, we use a broad definition of human capital including all employees in total employment with at least one vocational qualification.[9] Also, the regional export share as foreign turnover to total turnover for firms in the manufacturing sector is found to be positively correlated with the region's overall growth performance. While these results are rather clear cut, the estimated influence from variables proxying localization and urbanization advantages turns out to be ambivalent: While population density shows a clearly positive impact on growth, no significant correlation was found for regional sectoral specialization and external economies of scale proxied by the share of total employment in industries with high values for the Ellison–Glaeser index. Insignificant results were also found for the market potential (as sum of the own region's GDP plus neighborhood regions GDP, where the latter decays with distance) as well as the average regional accessibility from European agglomeration areas.

Summing up, the estimated conditional convergence equations are able to explain roughly 70 percent in the variation of productivity growth for German labor market regions. Generally, we observe that convergence forces are at work, indicating that initially poorer regions grow faster. The significance of factors controlling for the long-run technology level also shows that convergence is conditional rather than unconditional. Vocational qualification, regional knowledge stock, the regional economic structure, openness to world trade and population density turn out to be important drivers of the region's overall growth rate. With respect to GRW spendings, we find a significant positive marginal effect conditional on the region's initial income level. As shown in the theoretical section, without controlling for the positive transitory effect of funding, the estimated convergence rate among German labor market regions would be biased downwards. Our results show that the effect is higher for poor regions with a large gap to steady-state income. Here, the speed of convergence almost doubles. Investment subsidies are thus found to meet its (theory consistent) goal of fostering productivity growth in lagging regions and speed up convergence towards the regions 'own' steady-state.

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[9] We also tried alternative specification including only those employees as share of total employment with tertiary education. However, the results did not change much.

9.5 Model Extension to the Analysis of Spatial Effects

Recent contributions in the field of regional science have pointed to the empirical relevance of spatial dependencies in the analysis of income growth and convergence as well as spatial spillovers from regional policy instruments (see, e.g., Moreno and Trehan 1997; Fingleton 2001; Ertur and Koch 2007). This also led to various reformulations of the neoclassical growth model to properly account for spatial effects. Fischer (2010), for instance, augments the neoclassical framework to capture spatial spillovers by endogenizing the constant region-specific technology parameter a_i from (9.5) to account for spatially related technological interdependencies. The model basically assumes that the region i's technology level is a function of the technology level from regions in the direct proximity of region i.

In a similar vein, Egger and Pfaffermayr (2006) argue that the region's speed of convergence depends on its relative location in space and can be decomposed into three parts: One part measuring the region's own speed of convergence net of any spatial spillovers, and two remaining parts, which measure the importance of regional spillovers. The specification of regional spillovers implies that the region's labor productivity (growth) depends on the spatially weighted average of all other regions. In the spatial β-convergence model of Egger and Pfaffermayr (2006), spillovers stem from a remoteness effect (for common initial income gaps) and the effect of different starting positions (initial gaps).

Applications for (West) Germany such as in Niebuhr (2000), Funke and Niebuhr (2005) as well as Eckey et al. (2007) among others have shown that spatial effects driven by technological interdependencies indeed matter for regional growth and convergence processes. Moreover, there is a growing literature that aims at examining the spatial distribution of regional policies. Applied to the case of capital investment grants, De Castris and Pellegrini (2005) find for Italian regions that capital subsidies exhibit negative spillover effects to neighboring regions. A similar negative (though insignificant) result is reported in Eckey and Kosfeld (2005) for Germany.

Using quantitative tools, the analysis of spatial dependencies is typically conducted within the framework of spatial econometrics. Here, the most widely used model specifications are the spatial lag (also labeled spatial autoregressive, SAR) model and/or the spatial-error model (SEM). The main difference between the two approaches is the way in which spatial dependencies are assumed to operate. While the SAR model assumes that dependencies occur due to spillover effects from the endogenous variable, the SEM approach leaves the source of spatial autocorrelation undiscovered and simply accounts for the non-normality of the residuals by including a spatially weighted component in the total error term of the model. Applied to the neoclassical growth model, the SAR framework models growth rates to be inherently connected to each other, either in a positive or negative way depending on the estimated regression parameter for the spillover variable. Formally, the SAR model (in matrix notation) can be specified as follows:

$$y = a + \rho(W \times y) + dX + e, \tag{9.11}$$

where, next to the vector of regressors X, the spatial lag of the endogenous variable y is added. W in turn is a $(N \times N)$ spatial weighting matrix with matrix cells w_{ij}

measuring the pairwise distance for all combinations of cross-sectional units i, j and the coefficient ρ measures the degree of spatial spillovers, which arises from the spatialized endogenous variable defined as $\sum_{j=1}^{N} w_{ij} \times y_j$. The error term of the model is assumed to be well-behaved with zero mean and constant variance σ_e^2.

The SEM instead models spillovers to be of unknown exogenous source and all spatial effects are captured in the spatialized residual term as:

$$y = a + dX + \epsilon \quad \text{with } \epsilon = \lambda(W \times \epsilon) + \nu. \tag{9.12}$$

For empirical modelling the choice of implementing either (9.11) and (9.12) matters. As pointed out by Ward and Gleditsch (2008), the selection cannot be made solely on statistical grounds since both models are non-nested. Rather, good a-priori expectations about the source of spillovers are important. The theoretical literature on the 'spatialization' of the neoclassical growth framework clearly points towards the direction of the SAR specification. However, this may only be one part of the story. Instead, as Eckey and Kosfeld (2005) and De Castris and Pellegrini (2005), for instance, have shown is that models may be inadequate in order to measure the impact of spatial spillovers arising from the policy instrument.

In the recent spatial econometric literature therefore extensions to the SAR and SEM framework have been proposed (see e.g. LeSage and Pace 2009). An extension to the SAR model that also allows for spillovers arising from the vector of explanatory regressors is the so-called Spatial Durbin model (SDM). The SDM takes the following general form:

$$y = a + \rho(W \times y) + dX + \omega(W \times X) + e. \tag{9.13}$$

The main advantage of the latter is to explicitly quantify any effect stemming from the implementation of the GRW in neighboring regions from the perspective of region i as $\omega_s\,(W \times s)$. However, one has to note that the effect of s is not directly accessible through ω_s given the simultaneous presence of ρ. Instead, LeSage and Pace (2009) propose the computation of summary statistics decomposing the total effect from a variable into its direct and indirect effect. While the computation in the SAR is somewhat easier given that it has a global multiplier, for the SDM case all spatial lags from X have to be incorporated. In the latter case interpretation becomes much more easy, if we are able to zero-out spillovers from the endogenous variables (that is $\rho = 0$) after all spillovers from the set of exogenous regressors have been included. In the SDM model spillovers from the endogenous variable have the characteristics of a 'catch-all' term, that arise from factors outside the modelling framework.

Thus, an alternative to the SDM is the Spatial Durbin Error model (SDEM), which may be seen as an extension to the SEM framework that allows obtaining a theoretically meaningful interpretation to spillovers arising from the set of regressors and catches all remaining spatial autocorrelation in the residual term

$$y = a + dX + \omega(W \times X) + \epsilon \quad \text{with } \epsilon = \lambda(W \times \epsilon) + \nu. \tag{9.14}$$

One of the main advantages of the SDEM framework is that the coefficients d and ω can be interpreted as direct and indirect effect arising from any variable x with no further transformation being necessary.

Summing up the above discussion, in terms of our empirical growth model the most general specification arises from (see e.g. Moreno and Trehan 1997; Tondl 2001)

$$\begin{aligned}\Delta y_i = {}& a - b \times \log(y_{i0}) + \sum_{j=1}^{k} c_j x_{j,i} + \gamma s_i + \xi[\log(y_{i0}) \times s_i] \\ &+ \rho\left(\sum_{j\neq i}^{N} w_{ij} \times \Delta y\right) + \kappa\left[\sum_{j\neq i}^{N} w_{ij} \times \log(y_{i0})\right] \\ &+ \sum_{l=1}^{k} \phi_l \left(\sum_{j\neq i}^{N} w_{ij} \times x_{l,i}\right) + \psi\left(\sum_{j\neq i}^{N} w_{ij} \times s_i\right) \\ &+ \omega\left(\sum_{j\neq i}^{N} w_{ij} \times [\log(y_{i0}) \times s_i]\right) + e_{i0,T} \\ \text{with} \quad & e_{i0,T} = \lambda\left(\sum_{j\neq i}^{N} w_{ij} \times e_{i0,T}\right) + \nu_{i0,T}, \end{aligned} \tag{9.15}$$

which embeds the following restricted specifications:

- SAR: $\kappa = \phi_j = \psi = \omega = \lambda = 0$,
- SEM: $\kappa = \rho = \phi_j = \psi = \omega = 0$,
- SDM: $\lambda = 0$,
- SDEM: $\rho = 0$.

In order to estimate models according to (9.11)–(9.14), the choice of an empirical operationalization for the spatial weighting matrix W is needed. Here, the spatial econometrics literature has proposed different ways to handle spatial dependence giving weight to distance decay. The simplest form is to assume a binary neighborhood matrix that takes the value of 1 if a certain criterion for spatial proximity is fulfilled and zero otherwise. One standard way is to choose common geographical borders as geographical discrimination criteria, but the choice is not limited in this dimension. Also, common cultural, institutional and other factors may determine direct neighborhood.[10] However, one potential shortcoming of binary weighting matrices is their strict classification of either being in or out. Alternative measures for spatial neighborhood may therefore be constructed using the metric distance (for instance in kilometers) among cross-sectional entities.

Distance decay may then either enter in a linear or exponentially growing way. To give an example, matrix entries for a linear distance decay typically take the form of $w_{ij} = (D^{-1})_{ij}$, while a non-linear relationship to distance can be proxied as $w_{ij} = \exp(-D \times k)_{ij}$, where D is the geographical distance between to

[10] Moreover, though typically restricted first-order neighborhood, higher ranks are also possible, implying that cross-sections are seen as neighbors of order N if they share a common border with other cross-sections of rank order N.

cross-sections i and j, k is the distance decay parameter. The latter can take values as $k \in [1, \ldots, \infty]$. Since distance based matrices may become quite complex, mixed distance-neighborhood concepts have also been proposed, which uses distance based thresholds to specify binary specifications of W (see, e.g., Badinger and Url 2002). Threshold based computations of W typically work in a sequential manner as:

$$w_{ij} = \begin{cases} 0 & \text{if } i = j, \\ 1 & \text{if } c_{ij} = 1, \\ 0 & \text{otherwise,} \end{cases} \tag{9.16}$$

where c_{ij} is the element of a $(N \times N)$ link matrix with

$$c_{ij} = \begin{cases} 1 & \text{if } i \text{ and } j \text{ are spatially linked to each other,} \\ 0 & \text{otherwise.} \end{cases} \tag{9.17}$$

The function c_{ij} thus marks the critical threshold for the maximal distance (in kilometers) between i and j for which both entities are still considered as neighbors. Threshold values can either be set according to theoretical guidelines or algorithm-based. In the following we apply an algorithm proposed by Badinger and Url (2002), which uses spatial statistics in order to find those points in space, for which spatial autocorrelation inherent to a variable is maximized (in our case, labor productivity growth). The algorithm builds on the G_i-statistic proposed by Getis and Ord (1992). Figure 9.6 shows the results of the algorithm-based search for maximizing the standardized test Z_{G_i}-statistics for G_i using the distance between German labor markets on an interval [25 km, 280 km]. Spatial correlation for labor productivity growth among labor markets shows a global maximum at 130 kilometers. This point is chosen as cutoff distance to discriminate between spatial neighbors and non-neighbors in binary type weighting schemes for W.

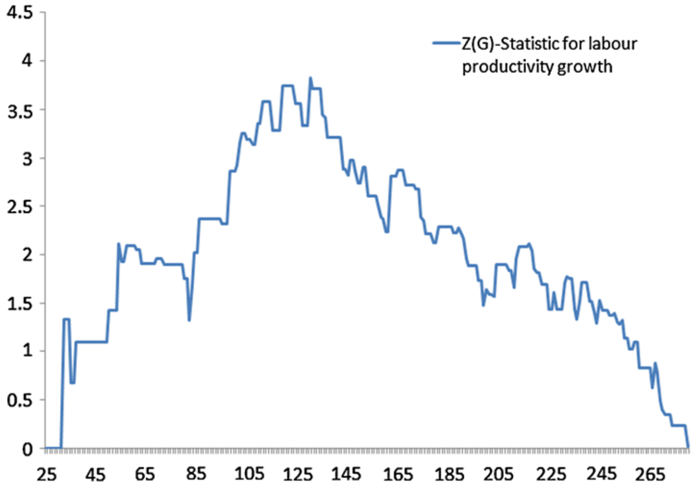

Fig. 9.6 Evolution of Getis–Ord G-statistic for alternative threshold distances

Table 9.4 Tests for spatial autocorrelation in the OLS residuals

Model	*Residuals from OLS*	*Residuals from OLS*
Spatial weighting matrix W	Linear metric	Optimal binary
Moran's I (Z_I-statistic)	2.48***	2.20**
Getis–Ord G (Z_G-statistic)		−2.24**

*Denote statistical significance at the 1% level **Denote statistical significance at the 5% level
***Denote statistical significance at the 10% level

Next to distance based weighting schemes using a linear and quadratic distance decay, we also use the optimal-binary weighting scheme according to the above described algorithm with threshold value 130 kilometers. All matrices are used in their row-standardized form according to

$$w_{ij}^* = w_{ij} / \sum_j w_{ij}. \tag{9.18}$$

Before moving to the computationally more complex spatial econometric models, we first check whether the standard aspatial regression approach shows any sign of misspecification in the error term of the model. Here we use the commonly known Moran's I test for spatial autocorrelation in the residuals (see, e.g., LeSage and Pace 2009). We take Specification III from Table 9.3 and apply both the linear metric as well as optimal binary concept for W. As the results in Table 9.4 show, we detect significant spatial autocorrelation in the OLS residuals. The results thus point to explicitly account for spatial dependencies in order to properly estimate the convergence equation for German labor markets and quantify the global effect of GRW support.

The results for the spatially augmented specifications are reported in Table 9.5. All equations are estimated using maximum-likelihood techniques. As with the aspatial model we start with the full set of control variables and additionally allow for different spatial lagged transformations in line with (9.11)–(9.14). Subsequently we restrict our attention to the set of control variables which turned out significant in the aspatial model plus those variables which in addition proved significant in the spatially augmented models. Table 9.5 only reports regression results for model specifications for GRW funding based on the binary dummy D_{GRW}. The results for GRW intensity turned out to be quite similar and are skipped for brevity.[11] Table 9.5 starts with the commonly applied SAR and SEM approach and allows for further channels for spatial interdependencies by estimating SDM and SDEM specifications.

In general, for all spatially augmented models, we see that the estimated coefficient for the set of regressors remains rather stable. This also accounts for the empirically estimated direct effect of GRW subsidies. The only notable difference

[11] Detailed regression tables for the latter can be obtained from the authors upon request.

Table 9.5 Spatial regression results for conditional convergence among German labor markets

Dep. var.: $(1/T)\log[y_{iT}/y_{i0}]$	V/ ML-SAR	VI/ ML-SEM	VII/ ML-SDM	VIII/ ML-SDEM
Initial labor productivity	-0.024^{***}	-0.024^{***}	-0.028^{***}	-0.029^{***}
$\log(Y94)$	(0.006)	(0.006)	(0.006)	(0.006)
Employment growth plus $(g+\delta)$	-0.006^{***}	-0.006^{***}	-0.007^{***}	-0.007^{***}
$\log(EWT)$	(0.002)	(0.002)	(0.002)	(0.002)
Investment intensity	0.006^{***}	0.005^{***}	0.005^{***}	0.005^{***}
$\log(S)$	(0.001)	(0.001)	(0.001)	(0.001)
Vocational training	0.012	0.015	0.029^{***}	0.030^{***}
$\log(HK)$	(0.010)	(0.010)	(0.011)	(0.010)
Share of manufacturing sector	0.004^{***}	0.005^{***}	0.007^{***}	0.007^{***}
$\log(IND)$	(0.001)	(0.001)	(0.001)	(0.001)
Share of high-tech industries	0.004^{**}	0.004^{**}	0.002^{*}	0.002^{*}
$\log(TECH)$	(0.001)	(0.001)	(0.001)	(0.001)
Market potential	0.002^{*}	0.002^{*}	0.003^{***}	0.003^{***}
$\log(MPOT)$	(0.001)	(0.001)	(0.001)	(0.001)
Population density	−0.007	−0.006	−0.005	−0.005
$\log(BVD)$	(0.005)	(0.005)	(0.005)	(0.005)
Squared population density	0.001	0.001	0.001	0.001
$\log(BVD^2)$	(0.001)	(0.001)	(0.001)	(0.001)
Dummy for GRW regions	0.071^{***}	0.081^{***}	0.085^{***}	0.081^{***}
D_{GRW}	(0.028)	(0.028)	(0.028)	(0.028)
Interaction term	-0.019^{***}	-0.021^{***}	-0.022^{***}	-0.021^{***}
$\log(Y94) \times D_{GRW}$	(0.007)	(0.007)	(0.007)	(0.007)
$W \times D_{GRW}$			-0.323^{**}	-0.276^{***}
			(0.005)	(0.103)
$W \times [\log(Y94) \times D_{GRW}]$			0.085^{**}	0.072^{**}
			(0.040)	(0.028)
$W \times \log(BVD)$			-0.020^{***}	-0.022^{***}
			(0.005)	(0.004)
ρ	0.073		0.240	
	(0.098)		(0.461)	
λ		0.561^{***}		−0.634
		(0.164)		(0.862)
log likelihood	863.55	866.32	873.88	874.06
Wald test of $\rho, \lambda = 0$	0.56	11.69^{***}	0.27	0.54
(p-value)	(0.45)	(0.00)	(0.60)	(0.46)
Moran's I	2.490^{***}	6.452^{***}	0.706	−0.147
(p-value)	(0.00)	(0.00)	(0.24)	(0.44)

Source: Standard errors in brackets
[*]Denote statistical significance at the 1% level [**]Denote statistical significance at the 5% level
[***]Denote statistical significance at the 10% level

stems from population density, which turns out to be insignificant for most specifications, as well as the skill level of regional employment which only shows a significant effect in the SDM and SDEM equations. On the contrary, market potential, which was estimated insignificantly in the OLS regressions, is found to be significant in the spatially augmented models. With respect to the spatial parameters ρ and λ in the SAR and SEM, respectively, Table 9.5 shows only statistical support for the SEM alternative. Further including spatial spillover effects from the vector of regressors X in the SDM and SDEM approach supports this result. Here, starting from a general approach and only keeping significant variables, besides the spatial lag of population density, also the spatial GRW dummy and—more important—the spatial lag of the interaction term $W \times (D_{GRW} \times y_{i0})$ turn out to be significantly different from zero. The interaction term thereby measures how far a policy-induced change in the convergence rate of neighboring regions translates to the region's own growth path. As Egger and Pfaffermayr (2006) have shown, we can thus augment (9.10) to measure the growth in labor productivity conditional on the relative gap to the steady-state level under the presence of spatial spillovers. The total spatially augmented net effect is then composed out of its aspatial and spatial element as

$$\Delta_{sn} y_i = \beta_{sn} \times (y^* - y_{it}). \tag{9.19}$$

The coefficient β_{sn} in turn can be obtained from the following relationship as $(\xi + \omega) = (1 - e^{-\beta_{sn} T})/T$ based on the gap between actual and steady-state income y^*. Given the positive regression coefficient ω, the results in Table 9.5 indicate that the spatially associated spillover effects from the GRW funding scheme is negative. These results are qualitatively in line with earlier results reported in Eckey and Kosfeld (2005). The graphical distribution of the spatial effect in line with the graphical inspection in the aspatial model is shown in Fig. 9.7. As the figure shows, the indirect spatial effect partly offsets the positive direct effect of funding, the downward shift is about one third of the original direct effect for regions far below their steady-state level. Here, the total effect from GRW funding is nevertheless still significantly positive. The more the region approaches its steady-state income level, the more dominates the negative indirect effect of the support scheme. However,

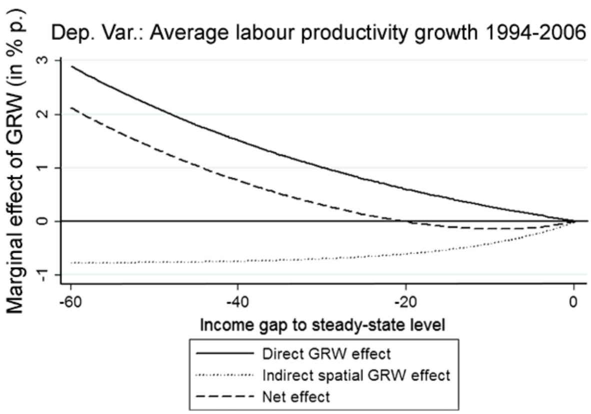

Fig. 9.7 Marginal effect of GRW subsidies relative to regional income gap

this only applies for income regions in which both effects of GRW funding also reduces in absolute terms, so that the negative overall distortionary effect of the GRW is rather small.

Finally, the plausibility of a negative indirect effect of the policy instrument has to be discussed. As Eckey and Kosfeld (2005) argue, one likely explanation is the role of spatial replacement effects due to changes in the relative capital investment prices among regions. In this line of argumentation, regions which receive funding become *ceteris paribus* more attractive compared to non-funded regions and are thus able to poach production factors from their neighbors. Our analysis shows that solely focusing on the direct effect of GRW funding overestimates its total effect since it ignores the poaching of factor inputs. Nevertheless, from an overall perspective, the net GRW impact is found to be positive arguing in favor of policy effectiveness, which aims to foster labor productivity growth in lagging regions. The inspection of the models' residuals finally shows that in the spatially augmented SDM and SDEM no misspecification from uncaptured spatial autocorrelation remains. Regarding the role of spatial spillovers from the endogenous and exogenous regressors, empirical support is given to the SDEM specification. We could not find statistical support for a further direct link through the spatial lag of labor productivity as 'catch-all' parameter, hence, the extension to a more subtle SDM is not required.

9.6 Conclusion

In this chapter, we have analyzed the role of physical investment subsidies and business related public infrastructure projects under the 'Joint Task for the Improvement of Regional Economic Structures' (GRW) for labor productivity growth among German labor markets between 1994 and 2006. We used an empirical specification guided by neoclassical growth theory, which allows for a temporary increase in the region's speed of convergence towards its long-run steady-state level to occur in the course of being supported. Next to the direct policy effect, we also accounted for the likely role of indirect spatial spillovers in a system of interconnected supported and not-supported regions.

Our empirical results show that the neoclassical growth model is an adequate vehicle for modelling growth and convergence processes among German labor markets. All estimated specifications indicate that spatial convergence forces are in order. Controlling for potential long-run driving forces of the regions technology level and in turn steady-state productivity level allows us to identify the GRW policy effect. Because enhancement of capital supply in lagging regions is the primary goal of the GRW scheme, in our empirical model we carefully design the null hypothesis of being tested as the policy induced change in the convergence rate towards long-run income. To do so, we construct an interaction term linking the convergence rate to the policy stimulus, which allows us to measure the change in the speed of convergence for funded over non-funded labor markets. This approach can be seen as an advantage over models, in which simply a measure for the policy input is added to the set of control variables for the long-run technology level. Instead, our specification is perfectly in line with the 'spirit' of neoclassical growth theory in which even a permanent increase in the physical investment rate may only exhibit a temporary effect on productivity growth, leaving the long-run growth rate unaffected.

Our results show that, on average, the GRW leads to an increase in the convergence rate, which is found to be the higher for those regions, whose income gap relative to steady-state productivity level is large. Accounting for spatial dependencies, we also apply different spatial econometric extensions to the neoclassical convergence model, which are capable of modelling spillover effects originating from the endogenous and exogenous variables in the regression setup. We find that negative indirect spillover effects of the GRW are in order. The obtained negative spillovers can be motivated by changes in relative prices for physical investment among regions and result in poaching of production factors from their neighborhood. However, the total effect of the GRW support scheme remains positive. This in turn indicates that the funding scheme is able to foster the growth dynamics of funded regions towards its long-run steady-state growth path.

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Chapter 10
Dynamic Consumption Models for German States: The Role of Excess Sensitivity to Income and Regional Heterogeneity in Adjustment

10.1 Introduction

The specification and estimation of consumption functions at different scales of aggregation is an integral part of empirical economic research. From a regional science perspective, one particular question to answer is whether and by what magnitude current income shocks hit regions asymmetrically. Gaining insights into the regional heterogeneity in adjusting consumption to current income changes may provide important guidance regarding the likely effectiveness and spatial distribution of demand side stabilization policies. For instance, although ultimately not implemented by the German government, one prominently advocated policy option to combat the 2008 economic breakdown was the distribution of so-called consumption or tax vouchers (rebates) in the spirit of earlier policy experiments in the USA and Japan (see e.g. Seidman 2003). According to macroeconomic theory, for such a temporary expenditure shock to work, consumers (or at least a large part of them) need to be either myopic or liquidity constrained. We take the Permanent Income Hypothesis (henceforth PIH) as analytical framework to test whether German consumers significantly depart from the model's predictions by adjusting consumption spendings to past and current temporary income shocks.

Recent empirical findings on German (regional) consumption data indeed find a substantial degree of "excess sensitivity" to income (see Dreger and Kosfeld 2003, and DeJuan et al. 2006). This latter result implies a rejection of the PIH, which rests on the assumption that representative agents plan consumption expenditures on the basis of their lifetime income expectations rather than period-by-period income. According to the PIH framework, agents should therefore not react to temporary income shocks if their expectations about lifetime (or permanent) income remain unchanged. In the empirical literature, various testing approaches for the appropriateness of the Permanent Income model with rational expectations have been applied. Besides the prominently debated issue of liquidity constraints, the notion of loss aversion and myopic consumers have become widely studied phenomena (see e.g. Shea 1995, as well as Bowman et al. 1999). Likewise habit formation, rule-of-thumb consumers or social norms may motivate a deviation from the strong rational

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expectation assumption of the PIH framework. By an appropriate estimation design, different consumer characteristics can be identified.

In this chapter, we therefore tackle the above empirical findings for Germany in light of new theoretical and methodological work on the PIH approach. We adopt a regional perspective and use different samples based on German state-level data including a long time-series for West German states (1970–2007) as well as data for all German states including East Germany since re-unification (1991–2007). Using different sample may allow identifying structural differences in the consumption patterns of the West and East German macro regions. Starting with a short-run approach such as the standard workhorse model in the empirical PIH literature (see e.g. Hall 1978; Flavin 1981; Campbell and Mankiw 1989, 1990 and 1991), we do not find strong evidence for "excess sensitivity" in the context of a dynamic panel data model (with insignificant results for West Germany and mixed findings for the total German sample since 1991). Our preferred specification relates changes in consumption to a "surprise" term in permanent income, proxied by the residual of an autoregressive income process, as well as past values of consumption growth. Following Malley and Molana (2006) we can interpret this habit formation augmented specification as consumers' solution to a optimization problem with habit persistence.

In addition to the short run approach typically used in testing for the validity of the PIH framework, we also combine the long- and short-run perspective in a panel error correction model (Panel ECM). A stable long-run cointegration relationship between (real) income and consumption can be interpreted as a necessary condition for the validity of the PIH. Using panel cointegration tests in the framework of Westerlund (2007), we could clearly reject the null hypothesis of no cointegration between income and consumption. We are therefore able to specify a Panel ECM and look at the short run adjustment coefficients in the consumption equation to judge about the share of liquidity constraint households. Compared to the short-run approach, for both the West as well as total German sample we find a significant but much lower fraction of constrained agents as in Dreger and Kosfeld (2003). Our findings come close to earlier results for German data in Wolters (1992) and for the US as, e.g., in Fuhrer (2000).

Since we employ different estimators for the Panel ECM including dynamic fixed effects (DFE), mean group (MG) and pooled mean group (PMG) estimation we are also able to check for the asymmetry in the income-consumption path of German regions both with respect to the long- and short-run adjustment dynamics. From a methodological point of view, testing for the asymmetry of the different cross-sections (regions) in focus boils down to the question of equal slope coefficients in the short- and long-run coefficients of the consumption function. The design of the MG, PMG and DFE estimators allows for sequential testing for the validity of different cross-section restrictions. That is, starting from the consistent but potentially inefficient MG estimator we first test for the equality of the long-term coefficients using a standard Hausman test. Both for West Germany as well as total Germany our Hausman test statistic does not reject the null hypothesis of equal coefficient size for the different states and thus a homogeneous long run cointegration path.

However, short-run equality in the slope coefficient for current income changes is rejected for the total German sample since 1991. Aiming to get a deeper understanding of the heterogeneity of short-run adjustment of German states in their regional consumption path to a common long-run solution, we apply a partial clustering framework and employ testing strategies from the "club convergence"-literature such as proposed in Phillips and Sul (2007). At the heart of the testing strategy lies a series of Roy–Zellner tests, which starts from a cross-section ordering of estimated short-run coefficients and sieves the data for club members starting from the formation of an initial core group. This allows us to identify different short-run regimes within Germany.

Since spatial income and consumption correlations may be in order at the regional level, we run the same type of tests for spatially filtered variables. The latter may be seen as a robustness analysis to the aspatial benchmark estimation and allows controlling for external-habit formation in the data as well as the effect of cross-border shopping (see Korniotis 2010). For spatially filtered variables, the homogeneity of a common dynamic consumption function among German regions cannot be rejected at reasonable confidence levels, supporting evidence for a common dynamic consumption model among German states with a small share of excess income sensitivity between 10 and 12 percent.

The remainder of the chapter is organized as follows: In Sect. 10.2 we briefly review the theoretical underpinnings of the PIH framework as theoretical foundation and derive testable empirical specifications. Section 10.3 gives an overview of the chosen econometric approach. In Sect. 10.4, the different data samples employed are introduced and some stylized facts of income-consumption linkages are presented. In this section we also test the time-series properties of the variables. Section 10.5 reports the main empirical results for the short-run and cointegration analysis. Section 10.6 tests for the existence of regional asymmetries within a partial clustering framework. Here, we also present a sensitivity analysis, which accounts for the potential role of spatial autocorrelation in the data. We apply spatial filtering techniques to isolate the structural effects. Section 10.7 gives some concluding remarks.

10.2 The Permanent Income Hypothesis

The Permanent Income Hypothesis describes the optimal intertemporal behavior of a representative agent with an infinite time horizon.[1] It was first proposed by Friedman (1957) to establish a micro founded relationship between income and consumption. The main innovation to earlier consumption models such as the 'absolute' and 'relative' income hypotheses is that agents are assumed to plan expenditures on the

[1]Closely related, the Life Cycle Hypothesis (LCH) assumes that individuals consume a constant percentage of the present value of their life income, where the latter is based on a finite lifetime perspective.

basis of lifetime income expectations rather than income received period-by-period. That is, using a discrete time framework for any period t the agent chooses consumption C_{t+j} for all $j \geq 0$ to maximize the expected value of objective function $E_t[U_t]$ with:

$$U_t = U(C_t, C_{t+1}, \ldots, C_{t+j}, \ldots), \tag{10.1}$$

subject to a sequence of budget constraints (again $j \geq 0$)

$$W_{t+j+1} = (1 + r_{t+j})W_{t+j} + Y_{t+j} - C_{t+j}. \tag{10.2}$$

W is the real value of the stock of non-human wealth, r is real (after tax) interest rate and Y is real (after tax) labor income. As Malley and Molana (2006) point out, the solution to this problem yields a smoothing rule for the expected marginal utility of consumption

$$E_t\left(\frac{\partial U_t}{\partial C_{t+j+1}} - (1 + r_{t+j})\frac{\partial U_t}{\partial C_{t+j}}\right) = 0 \tag{10.3}$$

for $j \leq 1$. Given that the underlying utility function is time separable and agents assume a constant real interest rate to discount both future income and future utility of consumption, (10.3) implies that agent's expected consumption remains constant over times as

$$E_t C_{t+j} = C_t = Y_t^P, \tag{10.4}$$

where Y_t^P is defined as constant annuity income stream associated with the present value of agent's human and non-human wealth. This permanent income term can be derived from the budget constraint re-written in terms of its infinite lifetime version as

$$\sum_{j=0}^{\infty} \lambda^{j+1} C_{t+j} = W_t + \sum_{j=0}^{\infty} \lambda^{j+1} Y_{t+j}, \tag{10.5}$$

with $\lambda = 1/(1 + r)$ as constant rate of time preference. Then, solving for Y^P yields

$$Y_t^P = r\left(W_t + \sum_{j=0}^{\infty} \lambda^{j+1} E_t Y_{t+j}\right) = r \sum_{j=0}^{\infty} \lambda^{j+1} E_t C_{t+j}, \tag{10.6}$$

which can be rewritten as

$$Y_t^P = (1/\lambda)Y_{t-1}^P - ((1 - \lambda)/\lambda)\, C_{t-1} + V_t, \tag{10.7}$$

so that the only revisions V_t in the previously formulated plan are due to unexpected factors affecting the agents' income as

$$V_t = r \sum_{j=0}^{\infty} \lambda^{j+1} (E_t Y_{t+j} - E_{t-1} Y_{t+j}). \tag{10.8}$$

Following Hall (1978) and assuming rational expectations V_t will behave as an unpredictable error term with $E_{t-1} V_t = 0$. The rational expectation interpretation of the PIH has been to subject to extensive empirical testing in the recent past. Given the scope of this analysis, we focus on the empirical strand of the PIH literature in the following.

10.3 Outline of the Empirical Approach

10.3.1 The Short-Run Approach to Income and Consumption Changes

Testing the empirical validity of the PIH framework became popular in succession of the seminal work by Hall (1978) on its rational expectation formulation (RE-PIH). The underlying testable hypothesis of the RE-PIH builds on a 'surprise' consumption function, which typically implies estimating the following two-equation system (Flavin 1981) with variables in logs

$$Y_{i,t} = \alpha_0 + \sum_{l=1}^{k} \alpha_l Y_{i,t-l} + \gamma t + \epsilon_{i,t}, \tag{10.9}$$

$$\Delta C_{i,t} = \beta_0 + \beta_1 \Delta Y_{i,t-1} + \beta_2 \epsilon_{i,t} + u_{i,t}. \tag{10.10}$$

The system in (10.9)–(10.10) specified as a panel data model, where $i = 1, \ldots, N$ denotes the cross-section dimension and $t = 1 \ldots, T$ is the time dimension of the data. $Y_{i,t}$ is assumed to be a linear stochastic autoregressive (AR) process. In the consumption equation (in first differences) the surprise in permanent income is modelled in terms of observable income $\epsilon_{i,t} = (Y_{i,t} - E_{t-1} Y_{i,t})$. Accordingly, β_1 measures excess sensitivity of changes in consumption to income changes and β_2 is the warranted change in consumption given the proxy for innovation in the income process ($\epsilon_{i,t}$). Under the RE-PIH, innovation in labor income is assumed to be proportional to the surprise in permanent income ($Y_t^P - E_{t-1} Y_t^P$). If the RE-PIH approach is valid β_1, should be equal to zero. According to the "excess sensitivity" hypothesis $\beta_1 \neq 0$ may reflect liquidity constraints (e.g. credit rationing). A modification of the above system, which relaxes the strong assumption of pure rational behavior, models consumption growth as

$$\Delta C_{i,t} = \beta_0 + \beta_1 \Delta C_{i,t-1} + \beta_2 \epsilon_{i,t} + u_{i,t}. \tag{10.11}$$

As Fuhrer (2000) and Malley and Molana (2006) show, (10.11) can be interpreted as the solution to a life-cycle optimization problem with habit persistence (rule-of-thumb smoothing). In this model, β_1 measures the impact of habit formation. As Korniotis (2010) points out, habit is a time-varying subsistence value and typically takes one of two possible forms: For models in which the determinants of habit are internal to the consumer (internal habit), consumption habits are influenced by the own past. Likewise, for models in which habits are determined externally, consumption decisions are influenced by the behavior of others (see e.g. Gali 1994; Campbell and Cochrane 1999; Korniotis 2010). Both concepts result in a gradual adjustment of current consumption to a reference value. However, due to observational equivalence it may be hard to distinguish empirically between external and internal habit formation.[2]

In a series of papers, Campbell and Mankiw (1989, 1990, 1991) propose a generalization of the above described equation system, which allows to directly estimate

[2] Ways to do so are discussed in Sect. 10.6.

the fraction of myopic or liquidity constrained households on the one hand, and those households which behave in line with the PIH on the other hand. Following Campbell and Mankiw (1991) we assume that constrained agents set $\Delta C_{i,t} = \Delta Y_{i,t}$. We denote ρ as proportion of agents for whom the constraints are binding, and augment the ARIMA$(1, 1, 0)$ model of Malley and Molana (2006) in (10.11) as

$$\Delta C_{i,t} = \beta_0 + (1-\rho)\beta_1 \Delta C_{i,t-1} + (1-\rho)\beta_2 \epsilon_{i,t} + \rho \Delta Y_{i,t} + u_{i,t}, \qquad (10.12)$$

where, again, $\epsilon_{i,t}$ is the surprise term in income derived from (10.10). Although Campbell and Mankiw (1991) interpret ρ as liquidity constraints, it may also capture other effects that lead to a deviation from optimizing behavior assumed in the PIH framework. Shea (1995) and Bowman et al. (1999) propose a way to distinguish explicitly between different restrictions such as myopic behavior, loss aversion and liquidity constraints in the dynamic consumption equation as

$$\Delta C_{i,t} = \cdots + \rho^{+}(POS_{i,t})\Delta Y_{i,t} + \rho^{-}(NEG_{i,t})\Delta Y_{i,t} + \cdots, \qquad (10.13)$$

where POS is a dummy variable for periods in which $\Delta Y_{i,t} > 0$, and NEG is a dummy variables for periods in which $\Delta Y_{i,t} < 0$. Then, the following cases can be distinguished:

- Permanent Income Hypothesis: $\rho = \rho^{+} = \rho^{-} = 0$
- Myopia: $\rho = \rho^{+} = \rho^{-} > 0$
- Loss aversion: $\rho^{+} < \rho^{-}$; $\rho^{+}, \rho^{-} > 0$
- Liquidity constraints: $\rho^{+} > \rho^{-}$; $\rho^{+}, \rho^{-} > 0$

Thus, under myopia the ρs should be positive, significant and equal. According to Bowman et al. (1999) loss aversion describes situations, where households are more prone to correctly adjust their consumption upwards in response to an anticipated future increases in income than they are to lower their consumption in response to an anticipated decrease. This behavior can be motivated in different ways: For instance, it can be understood in terms of the principle of hierarchy of needs so that smoothing of income downwards may exhibit certain thresholds, which are associated with an abrupt and incommensurable loss in satisfaction (see van Treeck 2008). It can be expected that consumers try to avoid such a fall back at all cost, while they are always willing to move up to higher levels in the hierarchy of needs.

Alternatively it has been recognized that there is a kind of competition in consumption associated with the notion of "catching up with the Joneses" (see Robinson 1956; Gali 1994). When the individual's social status is linked to consumption, individuals will benefit from any increase in income to expand consumptions but will be reluctant to reduce consumption associated with falling behind the Joneses. The important testable implication is that $\rho^{+} < \rho^{-}$, since the reaction to negative *actual* income shocks should be larger given the growing gap between the household's rational expectations and actual "catching up with the Joneses"-behavior.

On the opposite case of liquidity constraints, ρ^{+} should be significantly positive and greater than ρ^{-}. When expected (permanent) income increases, consumers may not be able to increase consumption immediately in the absence of borrowing possibilities. But when the increase actually occurs, liquidity constraints are relaxed so that consumption grows strongly from one period to the next. When expected (permanent) income declines however, households can readily reduce consumption so that consumption growth will respond less to the change in actual income, when it finally occurs. Thus, under liquidity constraints ρ^{+} should be significant and larger than ρ^{-} as they prevent households from borrowing against higher *expected* future income.

Taking liquidity constraints as an empirically relevant example, the latter can be introduced to the above described theoretical optimization framework by simply including the following constraint $C_{i,t} \leq Y_{i,t} + W_{i,t}$. When the budget constraint applies, agents would like to smooth consumption but may not be able due to borrowing constraints so that the optimal consumption for each period is greater than cash at hand $(Y_{i,t} + W_{i,t})$. Under the assumption of cyclical behavior of current income, consumption is likewise expected to exhibit a volatile nature if the share of consumers subject to any of the above mentioned deviations from optimization behavior is sufficiently large. Thus, for policy making to empirically quantify the size of ρ may be of particular interest, since with a larger ρ also the likely effectiveness of short-term oriented demand stabilization policies increases.

To highlight the likely aggregate consumption path for different values of ρ, we set up a simple simulation model with two representative agents. One agent follows a lifetime optimization rule for consumption; the second agent faces a binding budget constraint for any period of his lifetime. The fraction of the latter agent in the total economy's consumption is measured by ρ. Given that income is subject to cyclical behavior, we can show the degree of consumption volatility for different scenarios with altering ρ. Further details about the simple simulation model are given in Appendix A. The results show that for large fractions of liquidity constraint households (e.g. $\rho = 0.9$ and $\rho = 0.6$), also consumption varies strongly in response to income changes. However, for moderate to small fractions, in particular $\rho = 0.3$ and $\rho = 0.1$ we already observe a significant smoothing of aggregate consumption, indicating the potentially limited role of demand oriented fiscal policies. In the following we take these simulation results as benchmark for the interpretation of our estimates for the degree of "excess sensitivity" in dynamic consumption models using German regional data.

Given the inclusion of lagged endogenous variables in both the income equation as well as consumption equation, when accounting for the habit formation as in Malley and Molana (2006), leads to a system of dynamic short run models. For estimation of such models, the panel econometric literature proposes different IV and non-IV estimators, which are able to properly deal with the likely problem of endogeneity between the lagged endogenous variable and the error term (see e.g. Baltagi 2008, for an overview). We apply different estimators including simple Pooled OLS (POLS), corrected Fixed Effects estimation (LSDVC) and IV-based GMM approaches (both Arellano–Bond, 1991, and Blundell–Bond, 1998). The latter GMM estimators are able to account for any correlation of the right-hand-side regressors with the error term of the model. In empirical operationalization, we approach sequentially and obtain the parameters for the auxiliary income equation in (10.9), compute the residuals $(\epsilon_{i,t})$ and include them in the short-run consumption function.

10.3.2 Long- and Short-Run Cointegration Analysis

Although common practice, modelling unexpected deviations from permanent income based on a univariate auxiliary equation, may nevertheless not be the best empirical strategy. An alternative way to model the income-consumption system from above is to start from a multivariate cointegration perspective. Cointegration among income and consumption implies that both variables co-move over time and that any deviation from the stable long-run path is only of temporary manner. As Dreger and Kosfeld (2003) point out, the PIH framework basically implies cointegration between consumption and income or a stationary saving rate. In fact, the PIH interpretation of the cointegration system of consumption and income builds on the assumption that the long-run path in the latter variable is driven by its permanent component, while current income change lead only to temporary deviations from this path. Note, however, that cointegration analysis can only provide a weak test for the validity of the PIH since stationarity of the saving rate is also consistent with several alternative specifications such as the Keynesian absolute income hypothesis. In this sense, besides testing for a cointegrated long-run relationship between income and consumption as necessary condition, still special attention should be devoted to the interpretation of the short-run coefficients, in particular $\Delta Y_{i,t}$.

As discussed above, the regression coefficient for lagged and actual income growth may be interpreted as the income share earned by myopic or liquidity constrained households, which deviate from rational behavior according to neoclassical consumption theory. The dynamic consumption function in a cointegration perspective can be written in the form of a stylized Panel error correction model (Panel ECM) as:

$$\begin{aligned}\Delta C_{i,t} &= -\phi(C_{i,t-1} - \gamma_{0,i} - \gamma_{1,i}t - \kappa_{1,i}Y_{i,t})_{i,t-1} \\ &\quad + \sum_{j=1}^{k} b_{1,j,i}\Delta C_{i,t-j} + \sum_{j=0}^{k} b_{2,j,i}\Delta Y_{i,t-j} + u_{i,t}, \qquad (10.14)\end{aligned}$$

where ϕ in (10.14) is the speed of adjustment parameter, which brings short-run deviations back to the long-run equilibrium. ϕ is expected to be statistically significant and negative in order for error correction to occur. The coefficients b_1 and b_2 measure the influence of short-run movements in the dependent and explanatory variables in the error correction presentation, where the index j measures the number of time lags included in the regression approach with $j = 0, \dots, k$. Using the long-run cointegration relationship can be seen as an alternative to the commonly used AR-based surprise income term in (10.9). The Panel ECM in (10.14) potentially allows to estimate individual regression coefficients for each individual cross section i.

Before we are able to estimate the Panel ECM from (10.14), we first have to check for the existence of a stable cointegration relationship among the variables. Given the latter, we are then able to estimate Panel ECM for the consumption model. As estimators we use dynamic Fixed Effects (DFE) and Pooled Mean Group (PMG, see Pesaran et al. 1999). The main difference between the two estimators is that the DFE model assumes homogeneity of the short (ϕ, b_1, b_2) and long-run parameters (γ, κ) in the panel, while the PMG estimator allows for short-run heterogeneity over the cross-sectional units. In analogy to the short-run analysis in the above section, we can test for the significance of liquidity constrained agents as a fraction of all agents (ρ) measured by $b_{2,i}$.

Taking a closer look at different estimators for heterogeneous dynamic panel data models, they can be classified regarding their imposed long- and short run restrictions as:

- Mean Group (MG) estimator calculates short and long run parameters ($\hat{\hat{\phi}}, \hat{\hat{\kappa}}, \widehat{\widehat{b_m}}$) as unweighted means of individual coefficients (with variance $\hat{\hat{\Delta}}_{\hat{\hat{x}}}$ for each variable x) such as (see Pesaran and Smith 1995)

$$\hat{\hat{\phi}} = \frac{1}{N}\sum_{i=1}^{N}\widehat{\phi_i}, \tag{10.15}$$

$$\widehat{\widehat{b_{m,j}}} = \frac{1}{N}\sum_{i=1}^{N}\widehat{b_{m,j,i}} \quad \text{with } b_{m,i} = b_{1,1,i}, \ldots, b_{1,k,i}, b_{2,1,i}, \ldots, b_{2,k,i}, \tag{10.16}$$

$$\hat{\hat{\kappa}} = \frac{1}{N}\sum_{i=1}^{N}\hat{\kappa}_i, \tag{10.17}$$

$$\hat{\hat{\Delta}}_{\hat{\hat{x}}} = \frac{1}{N(N-1)}\sum_{i=1}^{N}(\hat{x}_i - \hat{\hat{x}})^2 \quad \text{with } x = \phi, b_m, \kappa. \tag{10.18}$$

- PMG constrains long-run parameters to be identical, while there are no constraints on the short-run parameters[3]

$$\hat{\kappa} = \hat{\kappa}_i \quad \forall i, \tag{10.19}$$

$$\hat{\hat{\phi}} = \frac{1}{N}\sum_{i=1}^{N}\hat{\phi}_i, \tag{10.20}$$

$$\widehat{\widehat{b_{m,j}}} = \frac{1}{N}\sum_{i=1}^{N}\widehat{b_{m,j,i}}. \tag{10.21}$$

- DFE finally constrains short- and long-run parameters to be identical for all cross-sections

$$\hat{\kappa} = \hat{\kappa}_i \quad \forall i, \tag{10.22}$$

$$\hat{\phi} = \hat{\phi}_i \quad \forall i, \tag{10.23}$$

$$\widehat{b_{m,j}} = \hat{b}_{m,j,i} \quad \forall i. \tag{10.24}$$

Since Pesaran and Smith (1995) have shown that the MG estimator is a consistent (although potentially inefficient) estimator, we can use it as empirical benchmark to test for the validity of cross-section restrictions in the long-run equation of the PMG and DFE using standard Hausman-type tests (see e.g. Hsiao and Pesaran 2007). Additionally, in order to analyze the likely heterogeneity in short-run adjustment more in depth, we apply a set of F- or χ^2-tests in the spirit of the Chow- or Roy–Zellner-

[3]The PMG estimator applies ML estimation for both the long- and short-run coefficients by maximizing the concentrated likelihood, see Pesaran et al. (1999) for details.

type 'poolability' tests (see e.g. Bun 2004; Pesaran and Yamagata 2008, as well as Baltagi et al. 2008, for recent surveys). The difference between the standard Chow and the Roy–Zellner tests rests on the assumption about the error term $u_{i,t}$ for the panel data model in (10.14). The Chow test treats the residuals as $u \sim N(0, \sigma_u^2 I_{NT})$ and assumes that individual effects are absent, where I_{NT} is an identity matrix of dimension $N \times T$. For models with error component structure thus a more general form of the variance-covariance matrix (Ω) is required. Baltagi et al. (2008) show that a generalized test described and applied by Roy (1957) and Zellner (1962), respectively, may be an appropriate choice.[4]

For the Chow and Roy–Zellner based testing approach we use both standard asymptotic as well as bootstrapped versions of the test. The latter specification has been recently proposed by Bun (2004). The author shows by means of Monte Carlo simulations that test statistics based on asymptotic procedures may be severely biased, when applying these tests to a limited number of cross-sections. The null hypothesis of the test statistics for coefficient equality on $\Delta Y_{i,t}$ in (10.14) is

$$H_0 : b_{m,1} = b_{m,2} = \cdots = b_{m,N} \quad \text{with } i = 1, \ldots, N, \tag{10.25}$$

and similar for the coefficient of the error correction term (ϕ). Inference on the size-corrected bootstrap alternative of the tests can then be made according to

$$\text{reject } H_0 : b_{j,1} = b_{j,2} = \cdots = b_{j,k} \quad \text{if } F > F^{*,1-\alpha}, \tag{10.26}$$

where $F^{*,1-\alpha}$ is the $(1-\alpha)$-quantile of the bootstrap distribution of the Chow F-test (and in the same manner for the Roy–Zellner Wald-type χ^2 test). For the bootstrap based inference we apply the resampling scheme outlined in Bun (2004) and use 1000 replications with a fixed seed number. In the bootstrap scheme we keep the values of exogenous regressors as before, while for the case of the lagged dependent variable, we condition on the first observation and construct pseudo values for the remaining observations iteratively. Summing up, the use of heterogeneous dynamic estimators allows to check for the homogeneity versus heterogeneity of regional consumption paths 'on-the-fly'.

In the following, we apply both the short-run and cointegrated Panel ECM approach to test for the significance and size of "excess sensitivity" in German regional data.

10.4 Database and Variable Description

For empirical estimation we use German state-level data (NUTS1 level). We design two different sample settings: First, we employ a long time-series for the 10 West German federal states between 1970 and 2007. Second, we use data for all 16 German states after re-unification starting from 1991 to 2007. Using the two different samples may allow identifying structural differences in the consumption patterns of the West and East German macro regions. We construct per capita time series in real terms for consumption (C) and GDP (Y). The data is gathered from the German Na-

[4]Where $\Omega = \sigma_\mu^2 (I_N \otimes J_T) + \sigma_\nu^2 (I_N \otimes I_T)$ and $J_T = e_T e_T'$ with e_T as a vector of ones for dimension T.

tional and State-Level Statistical Offices (*Volkswirtschaftliche Gesamtrechnung der Länder,* VGRdL 2010). For empirical estimation all variables are transformed into logarithms. Before we turn to the estimation exercise, we first present some stylized facts. Over the sample period, on average private consumption accounts for 55% of GDP (in real per capita terms) with a minimum of 36% for Hamburg, maximum of 65% in Lower Saxony.

As Table 10.1 shows, annual growth rates of GDP are found to be more volatile than consumption changes for different sub-periods, where volatility is measured in terms of the variables' standard errors around the sample mean for each displayed sub-period. This first result does not feed the hypothesis of "excess sensitivity". Figure 10.1 plots the level of real per capita GDP and consumption for the 16 German states. The figure shows that both variables increase over time, while both variables show to follow a similar time pattern (thus giving a first indication of a potentially

Table 10.1 Volatility of consumption and income growth for different time periods

Source: Data from VGRdL (2010)

	1970–1980	1981–1990	1991–2000	2001–2007
ΔC	0.015	0.017	0.016	0.013
ΔY	0.021	0.018	0.021	0.015

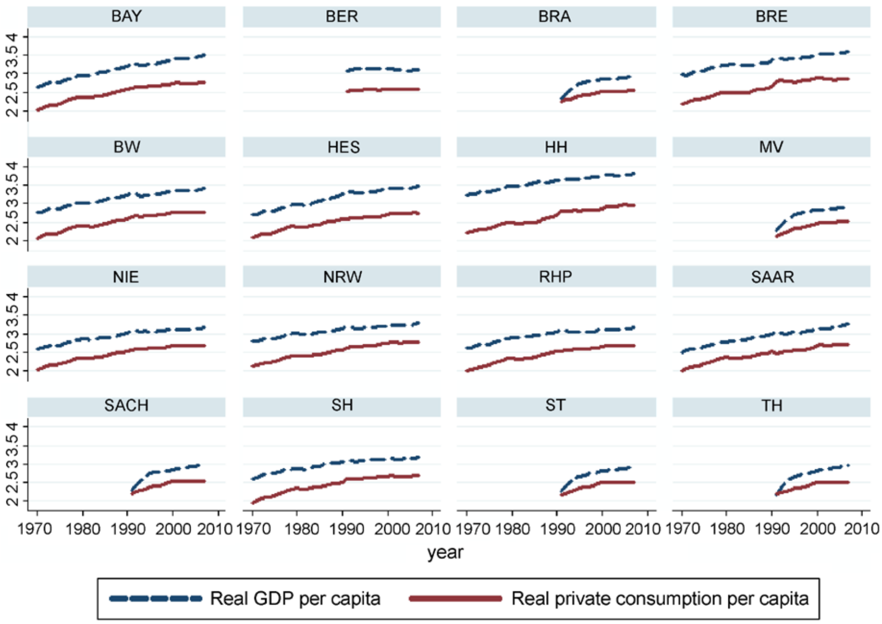

Fig. 10.1 Real consumption and GDP per capita for German states (in logs). *Source*: Data from VGRdL (2010). BW = Baden-Württemberg, BAY = Bavaria, BER = Berlin, BRA = Brandenburg, BRE = Bremen, HH = Hamburg, HES = Hessen, MV = Mecklenburg-Vorpommern, NIE = Lower Saxony, NRW = North Rhine-Westphalia, RHP = Rhineland-Palatine, SAAR = Saarland, SACH = Saxony, ST = Saxony-Anhalt, SH = Schleswig-Holstein, TH = Thuringia

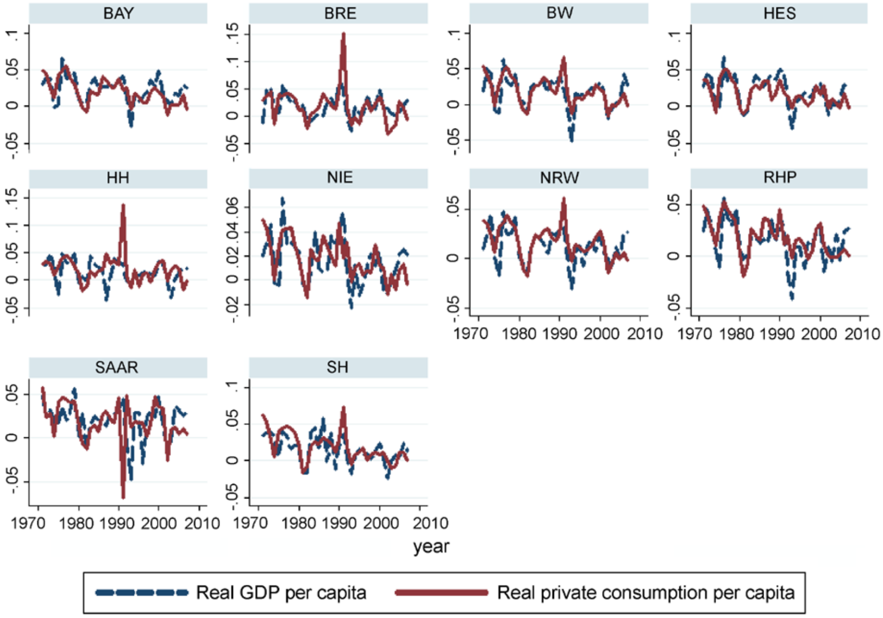

Fig. 10.2 Growth rate of consumption and GDP per capita (in %) for West German states. *Source*: Data from VGRdL (2010). Description see Fig. 10.1

stationary savings rate, as expected for cointegration of income and consumption). Figures 10.2 and 10.3 additionally plot for the two samples the annual growth rate of consumption and GDP in per capita terms, respectively. As Fig. 10.2 shows for the 10 West German states of the sample period 1970–2007, there is a positive correlation among output and consumption growth. The same holds for the shorter sample of 16 German states between 1991 and 2007. Here, consumption shows to have on average the smoother time pattern.

We also test for the time series properties of the variables. Here we apply the panel unit root tests proposed by Im et al. (2003) as well as Pesaran's CADF test (see Pesaran 2007). The advantage of the latter test is that it has been found to be more powerful in the case of cross-sectional dependences (see e.g. Baltagi et al. 2007). Taking the longer West German time series as empirical benchmark, the results in Tables 10.2 and 10.3 show that both income and consumption are integrated series of order $I(1)$, and thus turn stationary if transformed into first differences.[5] The results hold for variants of the tests with and without lag structure as indicated in Tables 10.2 and 10.3 respectively. Thus, in any case we are able to proceed with the short-run estimation strategy according to the equation system in (10.9) and (10.10). Whether we can also use long-run information in levels crucially depends upon the hypothesis whether the two variables are cointegrated. We will test for the latter in subsequent modelling steps.

[5]Results for the panel unit root tests for all 16 states can be obtained from the authors upon request.

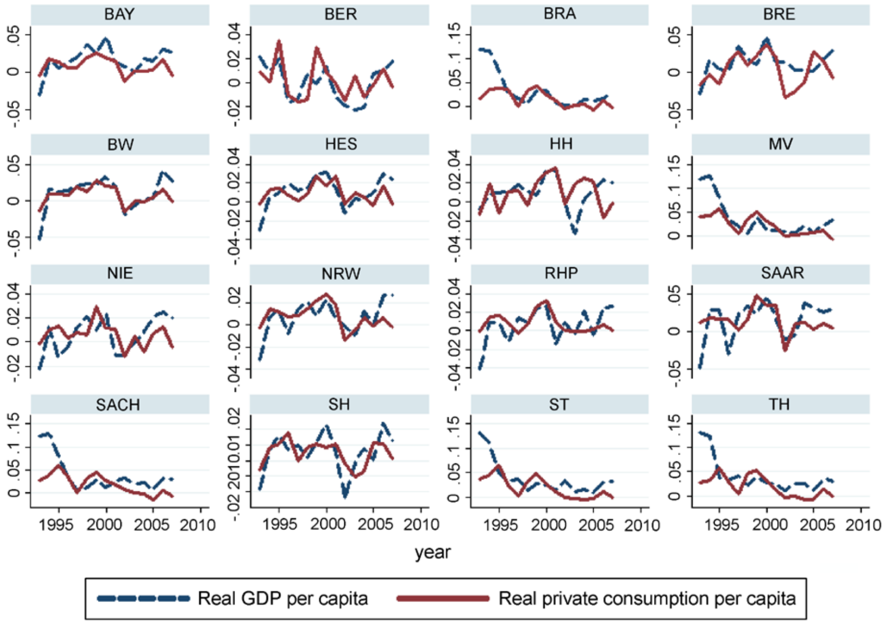

Fig. 10.3 Growth rate of consumption and GDP per capita (in %) for all German states. *Source*: Data from VGRdL (2010). Description see Fig. 10.1

Table 10.2 IPS panel unit root test for variables in levels and 1 diff.

	IPS t-bar test $N, T = 10, 38$ (lev.); 10, 37 (diff.)			
	H_0: Series non-stationary			
	Variant 1		Variant 2	
	W[t-bar]	(p-val.)	W[t-bar]	(p-val.)
$Y_{i,t}$	1.831	(0.96)	0.113	(0.54)
$\Delta Y_{i,t}$	-15.11^{***}	(0.00)	-8.820^{***}	(0.00)
$C_{i,t}$	-2.089^{**}	(0.02)	-0.046	(0.48)
$\Delta C_{i,t}$	-17.71^{***}	(0.00)	-8.820^{***}	(0.00)

Note: Variant 1 = lag(0), constant; variant 2 = lag(1), constant. The tests have been performed using the *ipshin* Stata-routines written by Bornhorst and Baum (2007)
*Denote statistical significance at the 10% level **Denote statistical significance at the 5% level
***Denote statistical significance at the 1% level

10.5 Empirical Estimation

10.5.1 Results for the Short Run Approach

- *West Germany* 1970–2007

We start with the short-run estimation approach for the West German sample. We estimate the system of (10.9) and (10.10) by alternative estimators for dynamic

Table 10.3 Pesaran CADF unit root test for variables in levels and 1 diff.

	CADF t-bar test $N, T = 10, 38$ (lev.); 10, 37 (diff.)			
	H_0: Series non-stationary			
	Variant 1		Variant 2	
	Z[t-bar]	(p-val.)	Z[t-bar]	(p-val.)
$Y_{i,t}$	−0.052	(0.48)	0.462	(0.68)
$\Delta Y_{i,t}$	−12.55***	(0.00)	−6.424***	(0.00)
$C_{i,t}$	−1.276	(0.10)	1.327	(0.91)
$\Delta C_{i,t}$	−13.16***	(0.00)	−7.957***	(0.00)

Note: Variant 1 = lag(0), constant; variant 2 = lag(1), constant. The tests have been performed using the *pescadf* Stata-routines written by Lewandowski (2007)

*Denote statistical significance at the 10% level **Denote statistical significance at the 5% level

***Denote statistical significance at the 1% level

panel data. The obtained parameter estimates turn out to be quite similar, both for the auxiliary income as well as dynamic consumption equation.[6] Given the superior performance found in various Monte Carlo simulation studies (see, e.g., Soto 2007), we report the Blundell–Bond System GMM (SYS-GMM) results in the following.[7] We start from a standard specification (including ϵ_{it} and $\Delta Y_{i,t-1}$) as typically used to test for the validity of the PIH (see e.g. Malley and Molana 2006) and subsequently augment the specification by lagged values of ΔC as well as current rather than lagged values of ΔY. We use a maximum pool of instrumental variables ranging from lag(2) to lag(4) and decide about the final set based on statistical criteria such as the J-statistic.[8]

The estimation results are shown in Table 10.4. The results show that $\epsilon_{i,t}$ as measure of surprise in permanent income turns out to be significant and of expected sign in most specifications. In the basic equation in column I of Table 10.4 also lagged income changes are found to affect consumption growth significantly. These findings would imply at least a partial rejection of the strict form of the Permanent Income Hypothesis with rational expectations. However, allowing for internal habit formation in column II changes the general picture. The results show that

[6]In the following, we only report results for the main consumption equation; regression details for the auxiliary income equation are given in Table 10.16 in Appendix B. The reported unit root tests in Appendix B show that the obtained residuals from alternative income specifications are uniformly tested to be stationary and can thus be used as regressor in the dynamic consumption model. Moreover, the regression exercise further underlines the results from the panel unit root tests reported above, namely that state income in levels is non-stationary with an autoregressive long-run coefficient close to one. The reader further has to note that the income equation was estimated in its level form rather than transforming the data as in the ARIMA approach. We do so in order to stay as close as possible to the original empirical framework in Flavin (1981).

[7]Further regression results can be obtained from the author upon request.

[8]The suggestion to start with a minimum lag length of two periods for each variable is taken from Campbell and Mankiw (1991) to avoid likely endogeneity problems.

Table 10.4 Short-run estimates of $\Delta C_{i,t}$ for West Germany (1970–2007) using SYS-GMM

Model	I	II	III	IV	V
Constant	0.01^{***}	0.01^{***}	0.01^{***}	0.01^{***}	0.007
	(0.001)	(0.001)	(0.001)	(0.002)	(0.006)
$\Delta Y_{i,t-1}$	0.17^{***}	0.08			
	(0.047)	(0.089)			
$\Delta Y_{i,t}$					0.16
					(0.365)
$\Delta C_{i,t-1}$		0.22^{**}	0.25^{***}	0.18^{**}	0.45^{***}
		(0.085)	(0.044)	(0.080)	(0.131)
$\epsilon_{i,t}$	0.46^{***}	0.43^{***}	0.43^{***}	0.43^{***}	0.25
	(0.069)	(0.069)	(0.070)	(0.050)	(0.198)
$\Delta C_{i,t-2}$				0.03	
				(0.054)	
$\epsilon_{i,t-1}$				0.06	
				(0.076)	
Obs.	360	360	360	350	350
m_1	(0.02)	(0.02)	(0.02)	(0.02)	(0.04)
m_2	(0.07)	(0.88)	(0.36)	(0.92)	(0.16)
J-stat.	(0.28)	(0.69)	(0.34)	(0.17)	(0.25)

Note: We include collapsed IVs from lag(1) up to lag(4) in each regression equation. We apply two-step efficient, heteroscedasticity robust GMM estimation. m_1 and m_2 report p-values for the Arellano–Bond (1991) test for autocorrelation (m_i) with maximum number of lags i. J-stat. reports the p-values for the Hansen J-statistic of instrument exogeneity

*Denote statistical significance at the 10% level

**Denote statistical significance at the 5% level

***Denote statistical significance at the 1% level

the inclusion of ΔC_{t-1} renders ΔY_{t-1} insignificant. This in turn may hint at the fact that ΔY_{t-1} was merely capturing the omitted effect of habit formation in the data rather than capturing excess sensitivity to current income changes. In line with Malley and Molana (2006) we find that consumption may well be explained by an ARIMA$(1, 1, 0)$ specification (columns III and IV).

We also check whether the ARIMA$(1, 1, 0)$ remains robust against a more general specification of Campbell and Mankiw (1990) with a fraction of agents (ρ) being liquidity constrained. For the latter, we substitute lagged income growth by current changes. The results are shown in column V of Table 10.4. As before, we do not find significant "excess sensitivity" in the above PIH framework. This result contrasts Dreger and Kosfeld (2003), as well as DeJuan et al. (2006), who find "excess sensitivity" and interpret this result as "liquidity constraints" for a similar data sample. Finally, when testing for asymmetric consumption responses to current income changes according to Shea (1995), the restriction of equality of ρ_1, ρ_2 is not rejected by the data (with $\rho_1 = \rho_2$, $F = 2.06$ and p-value $= 0.18$). Thus, for the West German sample with a long time period between 1970 and 2007, the overall results of the short run estimation approach in Table 10.4 do not indicate any violation of the PIH approach, when we account for habit formation.

- *Total Germany* 1991–2007

We replicate the same estimation exercise for the sample of all 16 German states between 1991 and 2007. Here the results in Table 10.5 show a slightly different

Table 10.5 Short-run estimates of $\Delta C_{i,t}$ for Germany (1991–2007) using SYS-GMM

Model	I	II	III	IV	V
Constant	0.01***	0.01***	0.01***	0.003	0.01***
	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
$\Delta Y_{i,t-1}$	0.20***	0.13***			
	(0.041)	(0.035)			
$\Delta Y_{i,t}$					0.33***
					(0.068)
$\Delta C_{i,t-1}$		0.26***	0.35***	0.31**	0.23**
		(0.076)	(0.075)	(0.148)	(0.081)
$\epsilon_{i,t}$	0.17	0.13**	0.12	0.20*	−0.14**
	(0.108)	(0.063)	(0.089)	(0.103)	(0.056)
$\Delta C_{i,t-2}$				0.07	
				(0.081)	
$\epsilon_{i,t-1}$				0.02	
				(0.072)	
Obs.	240	240	240	224	224
m_1	(0.00)	(0.00)	(0.00)	(0.02)	(0.00)
m_2	(0.05)	(0.16)	(0.29)	(0.13)	(0.26)
J-stat.	(0.11)	(0.24)	(0.08)	(0.04)	(0.18)

Note: Standard errors in brackets. We include collapsed IVs from lag(1) up to lag(4) in each regression equation. We apply two-step efficient, heteroscedasticity robust GMM estimation. m_1 and m_2 report p-values for the Arellano–Bond (1991) test for autocorrelation (m_i) with maximum number of lags i. J-stat. reports the p-values for the Hansen J-statistic of instrument exogeneity

*Denote statistical significance at the 10% level

**Denote statistical significance at the 5% level

***Denote statistical significance at the 1% level

picture. For the basic estimation equation in column I, lagged income changes are significant. The surprise income term ϵ_{it}, although of expected sign, is now insignificant. Including the one-period lagged endogenous variable ($\Delta C_{i,t}$) in the model in column II, the coefficient turns out significant, which again supports the hypothesis that habit formation matters. In this specification, also the surprise term for permanent income changes is significantly positive. The same also holds for lagged income growths. The latter finding gives first evidence that for the total German sample between 1991 and 2007 excess sensitivity to predict income changes may be present. This is even more obvious for the Campbell–Mankiw equation in column V. Here current income changes turn out to be strongly significant, while the proxy for surprise in the permanent income is of reverse sign. Nevertheless, the fraction of excess sensitive consumers is with 33% still smaller compared to findings reported in the recent literature.

All specifications show a good performance in terms of post estimation tests. Both for the West German as well as the total German sample the Hansen (1982) J-statistic does not reject instrument exogeneity in the SYS-GMM model. There also no sign of autocorrelation in the time dimension of the model as indicated by the Arellano–Bond (1991) m_1- and m_2-statistic. For the total German sample we get some evidence of asymmetry in the estimated coefficient for income sensitivity of consumption. The restriction of equality of ρ_1, ρ_2 is rejected at the 5% significance level (with $\rho_1 = \rho_2$, $F = 5.48$ and p-value $= 0.04$). The estimated coefficient with

$\rho^- > \rho^+$ hint at the role played by loss aversion as found earlier by Shea (1995) for US data as well as Bowman et al. (1999) for a sample of OECD countries (including Germany with $\rho^- > \rho^+$). However, since we are not sure about the quality of the derived proxy for permanent income surprise, we further estimate the consumption functions in a combined short- and long-run cointegration approach.

10.5.2 Results for the Short- and Long-Run Cointegration Analysis

- *West Germany* 1970–2007

The goal of the above short-run regression exercise was to replicate the main empirical model of testing the pure RE-PIH and a modified version, which accounts for the role of habit formation, using German Panel data. However, since the model only uses short-run information and a univariate measure for surprise in permanent income, it may be an inefficient way to exploit all the information contained in the data for the relationship between consumption and permanent income. To further check for the robustness of the above findings, we thus move on to combine the long- and short-run modelling perspective. As Dreger and Kosfeld (2003) note, the PIH implies cointegration between consumption and income in the long-run. We thus first check for the long run co-movement of C and Y based on Westerlund's (2007) panel cointegration tests, starting with the long panel for the West German states between 1970 and 2007.

Westerlund (2007) proposes four different test statistics that rely on the error correction parameter in a conditional error correction model. The tests can be interpreted as a generalization of the standard time series approach as, e.g., outlined in Boswijk (1995). The null hypothesis of no cointegration is tested against the alternative of significant error correction for individual panel members or for the panel as a whole. Thus, the G_τ and G_α statistics in Table 10.6 test for the absence of error correction for all cross-sections against the alternative that at least for one cross-section unit i the error correction term turns out to be significant. We also compute

Table 10.6 Panel cointegration tests for income and consumption for West Germany

Specification	Test statistic	p-value
G_τ	-3.04^{***}	(0.00)
G_α	-7.74^{***}	(0.00)
P_τ	-8.28^{***}	(0.00)
P_α	-5.55^{***}	(0.00)

Note: Automatic Lag-selection based on the AIC. Calculations based on the *xtwest* Stata routine by Persyn and Westerlund (2008)

*Denote statistical significance at the 10% level **Denote statistical significance at the 5% level

***Denote statistical significance at the 1% level

Table 10.7 Estimation results of the Panel ECM for $\Delta C_{i,t}$ (West Germany)

	WG 70-07 MG	WG 70-07 PMG	WG 70-07 DFE	WG 70-07 MG	WG 70-07 PMG	WG 70-07 DFE
	Long run coefficient					
$Y_{i,t}$	0.97^{***}	0.80^{***}	0.87^{***}	0.90^{***}	0.75^{***}	0.78^{***}
	(0.118)	(0.019)	(0.100)	(0.168)	(0.050)	(0.128)
	Short run coefficients					
ϕ	-0.29^{***}	-0.15^{***}	-0.12^{***}	-0.17^{***}	-0.09^{***}	-0.07^{***}
	(0.023)	(0.035)	(0.021)	(0.026)	(0.017)	(0.017)
$\Delta C_{i,t-1}$	0.30^{***}	0.28^{***}	0.22^{***}	0.15^{***}	0.16^{***}	0.15^{***}
	(0.059)	(0.064)	(0.066)	(0.037)	(0.043)	(0.044)
$\Delta Y_{i,t}$				0.27^{***}	0.34^{***}	0.34^{***}
				(0.059)	(0.055)	(0.061)
$\Delta Y_{i,t-1}$	-0.10^{**}	-0.03	0.03			
	(0.048)	(0.051)	(0.045)			
$\rho^+ = \rho^-$	3.43^{*}	2.49	2.38	0.65	0.53	2.74^{*}
p-value	(0.07)	(0.12)	(0.12)	(0.42)	(0.46)	(0.10)
$\|m\|$-stat.		2.26	0.49		0.79	0.01
p-value		(0.13)	(0.61)		(0.37)	(0.98)

Note: Standard errors in brackets. The $|m|$-stat. is the Hausman test for the null hypothesis of consistency and efficiency of the PMG and DFE relative to the MG benchmark against the alternative hypothesis of inconsistency of PMG and DFE
*Denote statistical significance at the 10% level **Denote statistical significance at the 5% level
***Denote statistical significance at the 1% level

the Panel P_τ and P_α statistics, which test the null hypothesis of no cointegration against significant error correction for all cross-section units. The results of the four Westerlund (2007) panel unit root tests are reported in Table 10.6.[9]

As the table shows, all four tests statistics clearly reject the null hypothesis of no cointegration for either one cross-section unit or the whole panel. Given the supportive findings of the cointegration tests, we then specify a Panel ECM as in (10.14). Table 10.7 displays the estimation results for West German states between 1970 and 2007. We use the MG, PMG and DFE approach. Next to the parameter estimates, we also present a set of postestimation tests to guide statistical inference for imposing long- and short run restrictions to the model. The results are as follows. The coefficient measuring the speed of adjustment (ϕ) from short- to long-run is statistically significant in all cases and underlines the existence of a stable cointegration relationship between income and consumption. As in the short-run estimation setup

[9]For the likely case of cross-sectional dependence in regional data, Westerlund (2007) proposes to use robust critical values obtained through bootstrapping. In our case, they are perfectly in line with the asymptotical inference, so that we do not report them explicitly.

Table 10.8 Poolability tests for the short run parameters in the Panel ECM

Test	Asymptotic	Bootstrap based critical values		
		$\alpha = 0.10$	$\alpha = 0.05$	$\alpha = 0.01$
$Chow_{b_{\Delta Y}}$	$1.28 \sim F(9, 319)$	2.08	2.75	3.92
p-value	(0.25)			
$RZ_{b_{\Delta Y}}$	$12.98 \sim \chi^2(8)$	15.72	22.18	45.17
p-value	(0.12)			
$Chow_{\phi}$	$1.77 \sim F(8, 319)$	1.58	2.07	3.23
p-value	(0.08)			
RZ_{ϕ}	$15.95 \sim \chi^2(8)$	55.56	73.26	102.84
p-value	(0.04)			

Note: $Chow_{\phi}$, RZ_{ϕ} are the Chow and Roy–Zellner poolability tests for equality of ϕ_i, $Chow_{b_{\Delta Y}}$, $RZ_{b_{\Delta Y}}$ are the Chow and Roy–Zellner poolability tests for equality of the i-individual parameters for $\Delta Y_{i,t}$

from above lagged income turns out to be insignificant in PMG and DFE specification. The more rigorous form using current rather than lagged income changes as proposed by Campbell and Mankiw (1990, 1991) shows a significant fraction of liquidity constrained households. However, the obtained results are much smaller than those recently reported by Dreger and Kosfeld (2003) and closely match earlier findings ($\rho = 0.29$ for West Germany reported in Wolters 1992; $\rho = 0.26 - 0.29$ for US data in Fuhrer 2000). We do not get empirical evidence for an asymmetric response of consumption to positive and negative income shocks according to the test proposed by Shea (1995).

In all specifications Hausman m-statistic moreover favors the long-run restriction of slope homogeneity in PMG and DFE specifications. This indicates that all 10 West German states exhibit a common long-run cointegration relationship between income and consumption. We also check for potential regional heterogeneity in the short-run coefficients of the model. Table 10.8 reports the result for the Chow and Roy–Zellner version of the poolability F- and χ^2-test of the data. Besides asymptotical versions of the test statistic, we also report critical values from the bootstrap resampling exercise according to Bun (2004). The results in Table 10.8 show that for the individual short-run coefficients for $\Delta Y_{i,t}$, both the Chow as well as the Roy–Zellner test, do not reject the null hypothesis of poolability of the 10 West German states for reasonable confidence levels.

With respect to the error correction parameters, the Chow test rejects the null hypothesis of poolability only at the 10% level, both for the asymptotic as well as bootstrap based version. The results of the Roy–Zellner test are not that clear cut: While the standard test statistics rejects poolability at the 5% level, the bootstrap based alternative strongly favors poolability. Bun (2004) reports similar empirical evidence, where classical asymptotic tests and bootstrap procedures may lead to conflicting test outcomes. Especially, for data settings with moderate N relative to T the author finds that the asymptotic tests are too strict in terms of reporting too low p-values. The basic proposal of Bun (2004) in this situation is then to rely on the critical values from the bootstrap distribution, which may lead to accurate inference in finite samples. In doing so, we cannot reject slope homogeneity for the latter.

- *Total Germany* 1991–2007

We additionally estimate a Panel ECM for the sample of all 16 German states from 1991 to 2007. One motivation for doing so is to account for a potential structural break in the variables due to German re-unification and the question is: How does it affect regional consumption paths? Another open research question given the huge macro regional differences between East and West Germany is: Are the less wealthy regions in East Germany more liquidity constrained than their Western counterparts? Earlier results in Dreger and Kosfeld (2003) for West Germany indeed find a positive correlation between the shares of liquidity constrained household and the regional unemployment rate for instance.

As for the West German sample, we start with the computation of panel cointegration tests to check for the stable co-movement of income and consumption over time. The results in Table 10.9 are however less evident as the findings for the West German states in Table 10.6. Only P_τ rejects the null of no cointegration at the 5% significance level. However, since we are dealing with rather small dimensions of our sample data (both N and T), we are not sure about the power of the Westerlund test for two-sided small samples and take the statistical results in support of a cointegration relationship among the variables.[10] Table 10.10 then presents the results of the Panel ECM estimation.

The results of the Panel ECM for unified Germany between 1991–2007 show a significant coefficient for the error correction term (ϕ), which we take as further evidence for cointegration between income and consumption. However, the income coefficient in the long-run relation equation of the cointegration system is smaller and indicates a less tight relationship compared to the results of the West German

Table 10.9 Panel cointegration tests for income and consumption for Germany

Specification	Test statistic	p-value
G_τ	-1.33^{*}	(0.08)
G_α	-3.08	(0.73)
P_τ	-3.88^{**}	(0.05)
P_α	-1.99^{*}	(0.09)

Note: Lag selection based on the AIC. Calculations based on the *xtwest* Stata routine by Persyn and Westerlund (2008)

*Denote statistical significance at the 10% level **Denote statistical significance at the 5% level

***Denote statistical significance at the 1% level

[10] For instance, Wagner and Hlouskova (2010) conduct a large scale finite sample comparison for different testing approaches. Based on Monte Carlo simulations the authors conclude that the tests including the Westerlund (2007) approach may have low power for $T \leq 25$.

Table 10.10 Estimation results of the Panel ECM for $\Delta C_{i,t}$ (Germany)

	G 91-07 MG	G 91-07 PMG	G 91-07 DFE	G 91-07 MG	G 91-07 PMG	G 91-07 DFE
	Long run coefficient					
$Y_{i,t}$	0.59^{***}	0.44^{***}	0.55^{***}	0.15	0.37^{***}	0.56^{***}
	(0.078)	(0.036)	(0.046)	(0.369)	(0.054)	(0.062)
	Short run coefficients					
ϕ	-0.42^{***}	-0.31^{***}	-0.24^{***}	-0.31^{***}	-0.25^{***}	-0.21^{***}
	(0.045)	(0.043)	(0.025)	(0.047)	(0.038)	(0.033)
$\Delta C_{i,t-1}$	0.12^{*}	0.06	0.21^{***}	0.15^{***}	0.16^{***}	0.21^{***}
	(0.069)	(0.076)	(0.070)	(0.054)	(0.051)	(0.055)
$\Delta Y_{i,t}$				0.10^{*}	0.15^{***}	0.11^{***}
				(0.060)	(0.055)	(0.038)
$\Delta Y_{i,t-1}$	-0.02	0.08^{*}	0.04			
	(0.075)	(0.049)	(0.038)			
$\rho^{+} = \rho^{-}$	0.21	1.44	0.08	4.37^{**}	0.52	11.86^{***}
p-value	(0.64)	(0.23)	(0.77)	(0.03)	(0.47)	(0.00)
$\|m\|$-stat.		3.40^{*}	0.01		0.36	1.25
p-value		(0.07)	(0.99)		(0.54)	(0.26)

Note: Standard errors in brackets. The $|m|$-stat. is the Hausman test for the null hypothesis of consistency and efficiency of the PMG and DFE relative to the MG benchmark against the alternative hypothesis of inconsistency of PMG and DFE

*Denote statistical significance at the 10% level **Denote statistical significance at the 5% level

***Denote statistical significance at the 1% level

states. Interestingly, for the short-run dynamics of the model, also the amount of "excess sensitivity" is smaller compared to the West German sample. Here we only find an elasticity of 0.22, which can be interpreted as a fraction of 22% of consumers, which react to current income changes.

We get further evidence that for the whole German sample the response to income shocks is not equal for positive and negative income changes. Both the MG and the DFE specification based on current income changes reject the null hypothesis of a symmetric income response at the 5% significance level. For the disaggregated DFE-model as in Shea (1995) we get coefficients $\rho^{+} = 0.01$ (0.87) and $\rho^{-} = 0.48^{***}$ (0.00) with p-values in brackets. Since $\rho^{-} > \rho^{+}$ and only ρ^{-} turns out to be statistically significant, as argued above, this pattern in turn can interpreted as loss aversion, where we observe a stronger response to actual negative shocks but not the other way around (see e.g. van Treeck 2008).

Turning to the post estimation tests, with respect to the long run coefficients the Hausman m-statistic again shows that pooling the data leads to efficiency gains, while it does not affect the consistency of the PMG and DFE estimators relative to the MG benchmark. The results for the Chow and Roy–Zellner tests on the homogeneity of the short run coefficients are reported in Table 10.11. Here the Chow test does not indicate a rejection of the null hypothesis of slope homogeneity for

Table 10.11 Poolability tests for the short run parameters in the Panel ECM

Test	Asymptotic	Bootstrap based critical values		
		$\alpha = 0.10$	$\alpha = 0.05$	$\alpha = 0.01$
$Chow_{b_{\Delta Y}}$	$1.27 \sim F(15, 175)$	2.03	2.29	3.64
p-value	(0.22)			
$RZ_{b_{\Delta Y}}$	$26.08 \sim \chi^2(15)$	45.61	54.61	77.88
p-value	(0.03)			
$Chow_{\phi}$	$1.34 \sim F(15, 175)$	1.32	1.67	3.06
p-value	(0.18)			
RZ_{ϕ}	$27.66 \sim \chi^2(15)$	117.3	137.5	196.6
p-value	(0.02)			

Note: $Chow_{\phi}$, RZ_{ϕ} are the Chow and Roy–Zellner poolability tests for equality of ϕ_i, $Chow_{b_{\Delta Y}}$, $RZ_{b_{\Delta Y}}$ are the Chow and Roy–Zellner poolability tests for equality of the i-individual parameters for $\Delta Y_{i,t}$

both the error correction parameter ϕ as well as the coefficient for short run income responses $b_{\Delta Y}$.

But again, the picture is less ambiguous when applying the Roy–Zellner approach. Here standard asymptotic inference rejects the poolability of the data at the 5% significance value. However, the computed bootstrap critical values turn out to be very large, so that poolability cannot be rejected. This again may support the argument raised in Bun (2004) that standard inference tends to reject poolability too often. However, at least some concerns regarding the poolability of the data may still be in order. In the following, we aim to explore this potential heterogeneity more in depth. In doing so, we relax the strong assumption that either all cross-sections can be pooled together or none at all.

10.6 Consumption Responses to Income Shocks After Re-unification: Are There Different Regional Short-Run Regimes?

10.6.1 A Partially Clustering Framework

Dropping the 'all-or-nothing' implication of either full homogeneity or heterogeneity leads to a partially clustering framework for the analysis of panel data, where the population of cross-sections is grouped into clusters. Within each cluster parameter homogeneity is maintained, while the parameters are allowed to vary between clusters. The empirical literature on the partially clustering framework is still in its infancy. Among the few empirical references, Sarafidis and Weber (2009) propose an information-based criterion, which uses the residual sum of squares (RSS) of the estimated model as objective function. The number of clusters is then determined by the clustering solution that minimizes RSS subject to a penalty function that is strictly increasing in the number of clusters. Though being strongly consistent for large N, the algorithm is not equipped to handle a very small number of cross-sections.

We therefore adapt a testing routine from the literature of (growth) convergence clubs and apply clustering algorithms developed in this field. Particularly, we take up an approach which was proposed by Phillips and Sul (2007) and, for instance, applied to the identification of regional convergence clubs in Europe by Bartkowska and Riedl (2009). Phillips and Sul (2007) develop a panel data model that allows for a wide range of possible time paths and individual heterogeneity. Clustering is tested by means of a regression based convergence test. We adapt the method proposed by the latter authors and modify the sequential steps involved in cluster identification, so that it fits optimally to our research design. Our routine involves the following steps:

1. Estimate the short-run parameters for each cross-section separately and order them according to coefficient size.
2. Perform for the first k cross-sections ($k = 2$) a generalized Wald test (Roy–Zellner) for coefficient equality and add further units until the test for parameter restriction is rejected.
3. Form a second group from all cross-sections outside the first 'club' and test for parameter restrictions.
4. If rejected repeat steps 1–3 on remaining cross-sections to search for subgroups that form further clubs.

Additionally, we also run pairwise Roy–Zellner tests to search for slope homogeneity for each pair of the total German sample between 1991 and 2007. In this case, we first run an unconstrained regression model with individual slope coefficients and then impose pairwise restrictions on the parameters of interest. We apply the methods to the total German data for all 16 states, since this sample has shown the greatest doubts regarding full slope homogeneity with respect to short-run current income shocks. Figures 10.4 and 10.5 show surface plots of p-values for pairwise tests of short-run coefficient equality for ΔY based on Roy–Zellner and Chow-type test respectively. Regions are arranged in descending order according to their estimated coefficient for ΔY. Both figures indicate that there is a range of regions, for which the null hypothesis of slope homogeneity can be rejected with $p < 0.10$.

Plotting additionally the results of pairwise Roy–Zellner tests, the upper part of Fig. 10.6 displays the results for two West German states, Bavaria (BAV) and North Rhine-Westphalia (NRW). As the figures show, for both Bavaria and North Rhine-Westphalia we are able to identify a clear cluster of five East German regions, for which slope homogeneity can be rejected (with p-values close to zero). An opposite picture emerges, if we instead draw scatter plots for two East German states Saxony (SACH) and Thuringia (TH) in the lower part of Fig. 10.6. Now, slope homogeneity for most West German states (except Hamburg, Lower Saxony and Schleswig-Holstein) can be rejected, while common parameter restrictions hold for all five East German states.[11]

[11] Further pairwise plots show very similar patterns and are not reported here. They can be obtained upon request from the author.

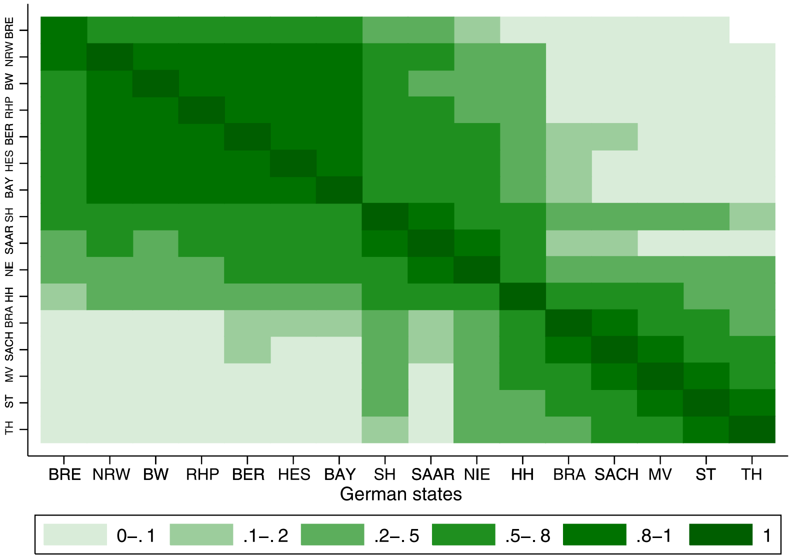

Fig. 10.4 Roy–Zellner test based surface plot of p-values for slope homogeneity of ΔY. *Note*: BW = Baden-Württemberg, BAY = Bavaria, BER = Berlin, BRA = Brandenburg, BRE = Bremen, HH = Hamburg, HES = Hessen, MV = Mecklenburg-Vorpommern, NIE = Lower Saxony, NRW = North Rhine-Westphalia, RHP = Rhineland-Palatine, SAAR = Saarland, SACH = Saxony, ST = Saxony-Anhalt, SH = Schleswig-Holstein, TH = Thuringia

Our partial clustering framework thus identifies two distinct 'clubs', which exactly match the West and East German macro regions (where the former includes Berlin). However, different to prior expectations, the results show that East German states are less driven by excess income sensitivity. Thus, the significant correlation found between other regional economic variables such as the unemployment rate (which is way higher in the East) and the degree of liquidity constrained households as reported in Dreger and Kosfeld (2003) for the West German states does not hold in the context of re-unified Germany. Instead, East Germans seem smooth consumption over the lifetime according to the PIH framework. However, when guessing about the likely causes for this empirical picture, it seems rather odd to assume different structural parameters for the underlying East and West German consumers. Instead, one likely explanation for this phenomenon is that the time smoothing of regional consumption paths in East German states is due to massive transfers from the West, which made the consumption pattern rather insensitive to short-run income shocks. Additionally, the East German economy is less open to foreign markets, so that external shocks affect production and final demand with smaller magnitude compared to the West. Similar results were are also reported for East German business cycle analysis, indicating that East German economic structure reacts less volatile both to short-run up- and down-swings of economic activity (see e.g. Ludwig et al. 2009).

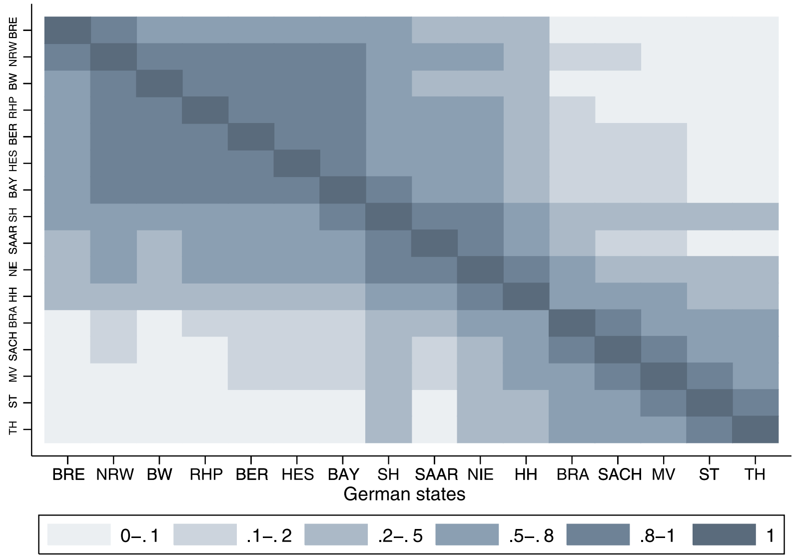

Fig. 10.5 Chow test based surface plot of p-values for slope homogeneity of ΔY. *Note*: BW = Baden-Württemberg, BAY = Bavaria, BER = Berlin, BRA = Brandenburg, BRE = Bremen, HH = Hamburg, HES = Hessen, MV = Mecklenburg-Vorpommern, NIE = Lower Saxony, NRW = North Rhine-Westphalia, RHP = Rhineland-Palatine, SAAR = Saarland, SACH = Saxony, ST = Saxony-Anhalt, SH = Schleswig-Holstein, TH = Thuringia

The two identified East and West German clusters can then be estimated separately, so that we are able to pool cross-sections within each cluster but allow for coefficient heterogeneity between the different clusters. The estimated dynamic consumption functions in the Panel ECM framework for both macro-regions are reported below (with standard errors in brackets). As before the share of excess sensitivity for the West German states is around 0.30. We do not get any sign of asymmetric consumption response for this subsample. However, for the pooled East German model we do so. As found for the aggregate model in Table 10.10, the East German short-run consumption is found to be strongly asymmetric. It is likely that the East German results also drive the aggregate German findings from above.

The result of the Shea (1995) test thus gives further empirical support to our hypothesis that the East German consumption pattern is partly driven by huge West–East transfers (or at least positive expectations about future transfer payments), which mimic a consumption behavior typically associated with loss aversion. In this sense, East German consumers are enabled to live in a “keep up with the Joneses” mentality relative to West German incomes. This results in an instantaneous correct anticipation of consumption patterns to future income prospect, while the reaction to negatively formed income expectations is sluggish (resulting in a stronger reaction if the income shock is actually realized). Nevertheless, this finding has to be interpreted carefully, since the sample has only few observations with negative income growth for East Germany.

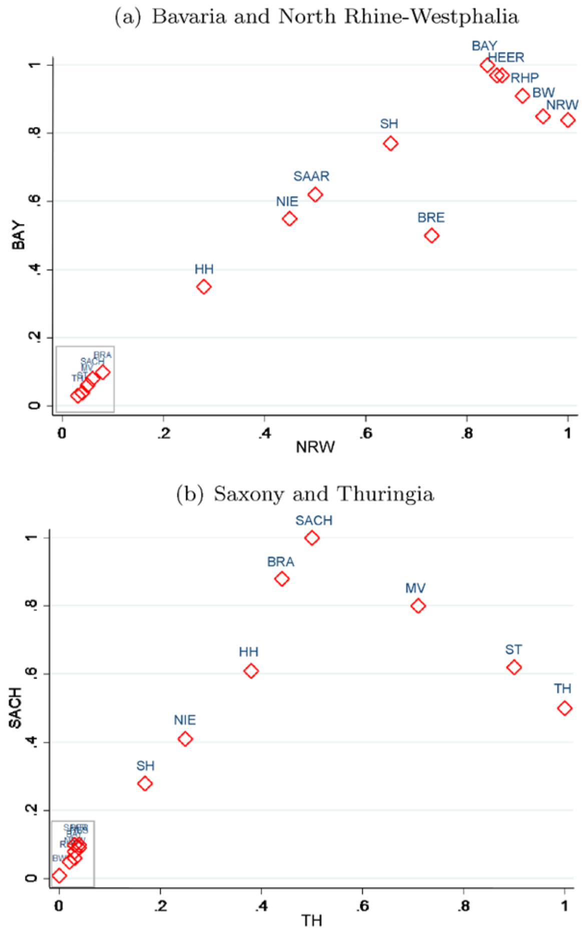

Fig. 10.6 Scatter plots for cluster identification according to Roy–Zellner test. *Source*: Based on p-values of pairwise coefficient tests. BW = Baden-Württemberg, BAY = Bavaria, BER = Berlin, BRA = Brandenburg, BRE = Bremen, HH = Hamburg, HES = Hessen, MV = Mecklenburg-Vorpommern, NIE = Lower Saxony, NRW = North Rhine-Westphalia, RHP = Rhineland-Palatine, SAAR = Saarland, SACH = Saxony, ST = Saxony-Anhalt, SH = Schleswig-Holstein, TH = Thuringia

- *West Germany*

$$\Delta C_{i,t} = \underset{(0.042)}{-0.17}\,(C_{i,t-1} - \underset{(0.122)}{0.45}Y_{i,t})_{i,t-1} + \underset{(0.065)}{0.12}\Delta C_{i,t-i} + \underset{(0.058)}{0.29}\Delta Y_{i,t-i} \tag{10.27}$$

- Shea (1995) asymmetry test for $\rho_1 = \rho_2$ is not rejected with: $\chi^2(1) = 0.02$ (p-value: 0.87).
- *East Germany*

$$\begin{aligned}\Delta C_{i,t} = &\underset{(0.051)}{-0.26}\,(C_{i,t-1} - \underset{(0.122)}{0.35}Y_{i,t}) + \underset{(0.092)}{0.22}\Delta C_{i,t-i}\\ &+ \underset{(0.417)}{0.56}(POS) \times \Delta Y_{i,t-i} - \underset{(0.079)}{0.14}(NEG) \times \Delta Y_{i,t-i}\end{aligned} \tag{10.28}$$

- Shea (1995) asymmetry test for $\rho_1 = \rho_2$ is rejected with: $\chi^2(1) = 2.71$ (p-value: 0.09). The aggregate ρ for East Germany was estimated insignificantly.

10.6.2 Robustness Check: Controlling for Spatial Dependencies

As a robustness check for the above results, we finally aim to control for the potential role of spatial dependence in the data. The latter may be important for two reasons: 1) As Korniotis (2010) recently found for US state level consumption data, the role of external habit formation as well as cross-border shopping may have an impact on the estimated model parameters. That is, the state's own consumption growth may be affected by consumption patterns of other states in the near distance. 2) The application of the clustering algorithm of Phillips and Sul (2007) assumes observations to be independent across sample units, significant spatial interdependency may thus affect the testing results. In an empirical application of the latter algorithm, Bartkowska and Riedl (2009) therefore use spatial filtering techniques prior to estimation on order to remove the spatial component inherent in regional data.

We follow this approach and apply the Getis (1995) spatial filtering methodology to remove any potential spatial autocorrelation from the data. Different from spatial econometrics, the idea to spatially filter the variables is similar to the idea of filtering out seasonality in time series data. We thus assume that we are able to decompose the original variable Y into a structural component Y^* and a purely spatial component S according to $Y^* = (Y - S)$. The Getis approach uses the local $G_i(d)$ statistic by Getis and Ord (1992). The approach requires a binary weighting matrix, which we define in terms of a neighborhood matrix that has cell entries equal to one, if two states share a common border and is zero otherwise. Details about the computation of the Getis spatial filtering approach can, e.g., be found in Getis and Griffith (2002).

In a first step we check for the presence of spatial autocorrelation for each variable using the total German sample for the period 1991 to 2007. Both for real per capita income as well as real per capita consumption we find that spatial autocorrelation is highly present and may thus introduce a potential bias to estimation. We then apply the Getis filtering approach to the original variables and denote filtered variables as "*". Table 10.12 reports the results for the original and transformed variables. As the table shows, the Getis approach is very effective in decomposing the variable into a structural component, which is free of any spatial autocorrelation.

While the Moran's I based Z-statistic reports a significant degree of spatial autocorrelation in the original variables (Y, C) for different sample years, the spatially filtered transformations (Y^*, C^*) do not show any remaining spatial dependence. We then use the filtered variables to re-estimate the Panel ECM from above. The results are shown in Table 10.13 together with post estimation tests for remaining spatial autocorrelation in the residuals of the model in Table 10.14.

The general result from the estimation output in Table 10.13 is that the estimated structural coefficients remain stable for the spatially filtered Panel ECM and turn out to be even more in line with the predictions of neoclassical consumption theory. That is, after controlling for likely role of external habit formation in addition to internal habit persistence, the share of "excess sensitivity" gets even smaller (ranging between 10 to 12%). As already argued above, the regression coefficient for $\Delta Y_{i,t}$ may thus rather be interpreted as a 'catch all' component for any omitted variable

Table 10.12 Z_I-statistic for spatial autocorrelation in income and consumption

Distance matrix	Common border			
year	Y	Y^*	C	C^*
2007	1.89**	−0.42	2.76***	0.18
p-value	(0.03)	(0.34)	(0.00)	(0.43)
2006	1.93**	−0.37	2.72***	0.14
p-value	(0.02)	(0.35)	(0.00)	(0.44)
2005	1.89**	−0.36	2.62***	0.09
p-value	(0.02)	(0.36)	(0.00)	(0.46)
(…)				
2000	2.19**	−0.06	2.82***	0.67
p-value	(0.01)	(0.47)	(0.00)	(0.25)
(…)				
1995	2.37***	1.07	3.17***	0.71
p-value	(0.00)	(0.46)	(0.00)	(0.24)
(…)				
1991	3.16***	0.54	3.25***	1.02
p-value	(0.00)	(0.31)	(0.00)	(0.15)

Note: Z_I is the Z-statistic for Moran's I distributed as $Z_I \sim N(0, 1)$. A '*' denotes that the variable has been spatially filtered based on the Getis (1995) approach

*Denote statistical significance at the 10% level

**Denote statistical significance at the 5% level

***Denote statistical significance at the 1% level

Table 10.13 Estimation results for spatially filtered Panel ECM

	G 91-07 F-MG	G 91-07 F-PMG	G 91-07 F-DFE	G 91-07 F-MG	G 91-07 F-PMG	G 91-07 F-DFE
	Long run coefficient					
$Y_{i,t}$	0.58***	0.68***	0.59***	0.68***	0.49***	0.60***
	(0.059)	(0.034)	(0.040)	(0.101)	(0.039)	(0.053)
	Short run coefficients					
ϕ	−0.44***	−0.30***	−0.27***	−0.34***	−0.26***	−0.23***
	(0.052)	(0.031)	(0.023)	(0.049)	(0.040)	(0.036)
$\Delta C_{i,t-1}$	0.26***	0.25***	0.22***	0.22***	0.21***	0.20***
	(0.075)	(0.075)	(0.088)	(0.070)	(0.070)	(0.057)
$\Delta Y_{i,t}$				0.06	0.12**	0.10**
				(0.056)	(0.053)	(0.045)
$\Delta Y_{i,t-1}$	−0.10	−0.06	−0.02			
	(0.079)	(0.056)	(0.041)			
$\rho_1 = \rho_2$	0.07	0.35	0.01	2.35	2.32	1.86
p-value	(0.79)	(0.55)	(0.95)	(0.12)	(0.12)	(0.17)
$\|m\|$-stat.		2.43	0.01		4.31	0.73
p-value		(0.12)	(0.99)		(0.03)	(0.39)

Note: Standard errors in brackets. The $|m|$-stat. is the Hausman test for the null hypothesis of consistency and efficiency of the F-PMG and F-DFE relative to the F-MG benchmark against the alternative hypothesis of inconsistency of F-PMG and F-DFE. "F" denotes that the regression is based on the spatially filtered model

*Denote statistical significance at the 10% level **Denote statistical significance at the 5% level

***Denote statistical significance at the 1% level

Table 10.14 Residual based Z_I-statistic of Moran's I using DFE estimators

Distance matrix	Common border	
year	$resid_{unfiltered}$	$resid_{filtered}$
2007	2.38***	−0.61
p-value	(0.00)	(0.27)
2006	2.39***	−0.55
p-value	(0.00)	(0.29)
2005	2.42***	−0.57
p-value	(0.00)	(0.28)
(...)		
2000	2.78***	−0.11
p-value	(0.00)	(0.46)
(...)		
1995	3.06***	0.22
p-value	(0.00)	(0.41)
(...)		
1992	3.55***	0.43
p-value	(0.00)	(0.33)

Note: Z_I is the Z-statistic for Moran's I distributed as $Z_I \sim N(0, 1)$
*Denote statistical significance at the 10% level
**Denote statistical significance at the 5% level
***Denote statistical significance at the 1% level

than as a effective measure for the degree of consumption sensitivity to short-run income changes. The Moran's I based post estimation test reported in Table 10.14 clearly shows that the unfiltered Panel ECM specification exhibits remaining spatial dependence in the residuals, while the filtered Panel ECM does not show any uncaptured spatial autocorrelation in the error term.

Finally, we are also interested on the impact of the spatially filtering approach on the poolability of the short-run parameters of the model. The results of the Chow and Roy–Zellner based test for slope homogeneity are reported in Table 10.15. The general result is that the poolability of the data cannot be rejected for the filtered model, in particular for the coefficient of $\Delta Y_{i,t}$. This result can be visualized by drawing a surface plot for the p-values of the pairwise poolability test for all 16 states. Figure 10.7 shows, that we cannot identify any particular cluster for which the null hypothesis of slope homogeneity can be rejected with p-values below 0.1.

Thus, using spatial filtered variables enables us to estimate an aggregate German dynamic consumption function with the following characteristics:

- Real income and consumption show to follow a stable cointegration relationship common to all regions; the speed of adjustment from short-run deviations to the long-run equilibrium is about 20–30% per year.
- The share of excess sensitivity leading to deviations from the PIH model augmented by (internal and external) habit formation is rather small, 10–12%.
- We do not find an asymmetric response with respect to positive or negative short-run income shocks (the test proposed by Shea 1995, does not reject the null of $\rho_1 = \rho_2$).

Table 10.15 Poolability tests for short-run parameters in spatially filtered Panel ECM

Test	Asymptotic	Bootstrap based critical values		
		$\alpha = 0.10$	$\alpha = 0.05$	$\alpha = 0.01$
$Chow_{b_{\Delta Y}}$	$0.66 \sim F(15, 160)$	1.76	2.06	2.57
p-value	(0.82)			
$RZ_{b_{\Delta Y}}$	$12.42 \sim \chi^2(15)$	32.99	40.21	49.15
p-value	(0.65)			
$Chow_{\phi}$	$0.77 \sim F(15, 160)$	1.28	1.55	2.58
p-value	(0.71)			
RZ_{ϕ}	$26.52 \sim \chi^2(15)$	77.16	94.23	139.13
p-value	(0.03)			

Note: $Chow_{\phi}$, RZ_{ϕ} are the Chow and Roy–Zellner poolability tests for equality of ϕ_i, $Chow_{b_{\Delta Y}}$, $RZ_{b_{\Delta Y}}$ are the Chow and Roy–Zellner poolability tests for equality of the i-individual parameters for $\Delta Y_{i,t}$

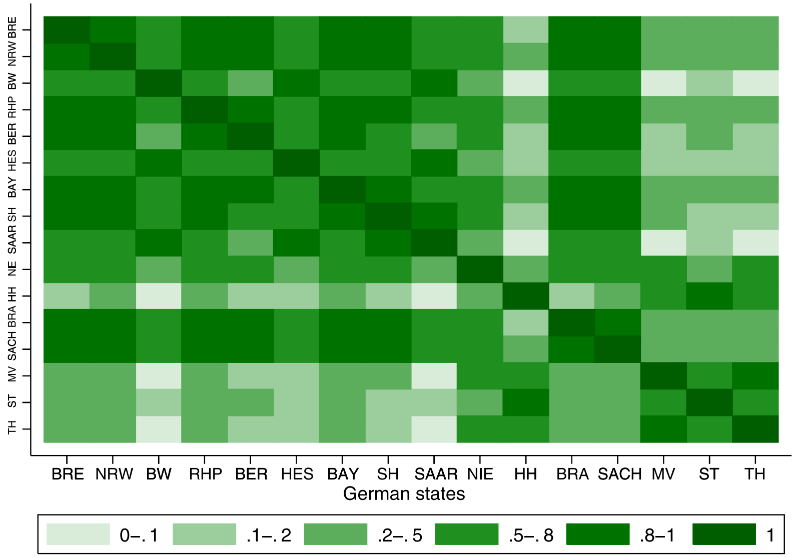

Fig. 10.7 Surface plot of p-values for slope homogeneity of ΔY in filtered model. *Note*: BW = Baden-Württemberg, BAY = Bavaria, BER = Berlin, BRA = Brandenburg, BRE = Bremen, HH = Hamburg, HES = Hessen, MV = Mecklenburg-Vorpommern, NIE = Lower Saxony, NRW = North Rhine-Westphalia, RHP = Rhineland-Palatine, SAAR = Saarland, SACH = Saxony, ST = Saxony-Anhalt, SH = Schleswig-Holstein, TH = Thuringia

10.7 Conclusion

We have estimated both short- as well as combined long- and short-run models for a dynamic consumption function of German states for different sample periods ranging from 1970 (and 1991 respectively) up to 2007. Our main research objective was to test for the validity of the neoclassical consumption theory and its implications for the effectiveness of discrete fiscal policies aiming at short-run demand stabilization. We have used a habit formation augmented specification of the Permanent Income Hypothesis to test for the statistical significance and size of excess sensitivity of consumption patterns to current income shocks. Our results show that for the short-run PIH model with habit persistence, we do not find any evidence for excess sensitivity of consumption to income changes among West German states between 1970 and 2007. The latter specification may thus be seen as an important extension to the pure RE-PIH framework.

However, the results become less clear cut for a sample of all German states starting from 1991. We find a significant, although quantitatively small coefficient for excess income sensitivity. To analyze the income-consumption relationship more in depth, making use of a combined long- and short-run perspective, we then specified up a panel cointegration framework. For both samples we get empirical support that income and consumption are co-move together in a stable long-run relationship. In the analysis of the short run adjustment dynamics of our specified Panel ECM we find a significant but smaller fraction of excess sensitivity than it was reported in the recent literature (our results hint to a share of around 30–35% compared to 45% in Dreger and Kosfeld 2003). Our findings match earlier results reported in Wolters (1992) who estimates $\rho = 0.29$ for West Germany as well as Fuhrer (2000) with $\rho = 0.26$ for US data.

The results hint at the limited effectiveness of fiscal policies to strengthen the demand side. In the conduct of this analysis, we are also particularly interested in investigating the degree of regional heterogeneity in the long- and short-run behavior of our dynamic consumption model. This may be important since the effectiveness of fiscal policies may not only depend on its mean effect, but also the regional distribution of the fiscal stimulus. For our data we get strong evidence for a common long-run equilibrium path between all German states. Regarding the short-run response to current income changes we find some statistical support for heterogeneous regional consumption adjustment. Using a partially clustering framework allows us to identify to distinct macro regional clusters, which are composed of the West and East German macro regions respectively. Here East German states are found to react less to current income changes than their West German counterparts. One likely explanation for this phenomenon is the time smoothing of regional consumption paths in East German states due to massive transfers from the West. Additionally, the East German economy is less open to foreign markets, so that external shocks affect production and final demand with smaller magnitude compared to the West.

As a robustness check we finally accounted for the potential bias introduced in the regression framework by spatial dependence of regional data. We applied the Getis (1995) method and re-estimate the Panel ECM based on spatially filtered variables. The results show that the estimated structural coefficients remain stable for the spatially filtered Panel ECM and turn out to be even more in line with the predictions of neoclassical consumption theory. That is, after controlling for likely role of external habit formation in addition to internal habit persistence, the share of excess sensitivity gets even smaller (ranging between 10 to 12%). This also raises doubts that Δy is an effective measure for excess income sensitivity as typically used in the aspatial empirical literature. Moreover, full poolability of the data is not rejected for the spatially filtered model. This allows us to estimate an aggregate German dynamic consumption function since re-unification with the following characteristics: Real income and consumption are cointegrated in the long-run, the speed of adjustment from short-run deviations to the long-run equilibrium is about 20–30% per year. The share of excess sensitivity is rather small. Finally, we do not find an asymmetric response with respect to positive or negative short-run income shocks.

Appendix A: A Simple Simulation Model for the Role of Liquidity Constraints in Driving Consumption Sensitivity to Income Changes

We use a small simulation model to analyze the quantitative impact of varying degrees of excess sensitivity of consumption to current income shocks. Perez (2000) sets up a representative agent model that is able to simulate household consumption smoothing according to neoclassical optimization theory. By adding binding liquidity constraints for certain time spans of the lifecycle, the model additionally exhibits consumption volatility as response to short-run cyclical behavior in the income pattern. Agents go through three phases of life: liquidity constrained, not liquidity constrained, retired. Positive changes in income can relax the liquidity constraint and lead to changes in consumption. However, due to lifetime optimization the increase in consumption is smaller than the income increase. To incorporate the possibility of cyclical behavior, Perez (2000) models the long-run path of an agent's expected income as upward sloping. A stylized graphical presentation of the lifetime income and consumption path is given in Fig. 10.8. In the figure, optimal consumption C^* is constant over the life cycle, T is the lifetime of the agent, R sets the retirement age. From this point on labor income drops to zero, which is highlighted in Fig. 10.8.

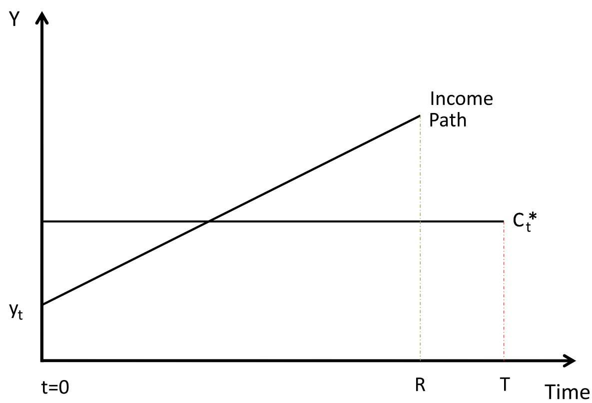

Fig. 10.8 Income and consumption for an unconstrained agent over lifetime

If the reader is interested in further details, he/she is referred to the original article by Perez (2000). For the research question analyzed in this study, we augment the model by introducing a second agent. The first agent still has the ability to borrow and build up a stock of wealth over his lifetime. Accordingly, this agent is able to smooth consumption according to $C_1(t) = C^*$. However, the newly introduced second agent faces a permanent liquidity constraint according to $C_2(t) = \max(0, Y_2(t))$ for every period. We then introduce the parameter ρ, which measures for the fraction of liquidity constrained agents in the total population. Labor income is distributed proportionally among the two agents as $Y(t) = \rho \times Y_2(t) + (1 - \rho) \times Y_1(t)$. The same holds for the composition of total consumption. We run simulations for different values of ρ.

Doing so, may give us an intuition, which impact a share of—say—50% of liquidity constrained households has on the volatility of aggregate consumption. The results for different parameter values of ρ are shown in Fig. 10.9. As the figure shows, while shares between 50 and 90% result in a very volatile consumption path, shares between 10 to 30% lead to a significant smoothing of consumption over the lifetime in line with the predictions of the Permanent Income Hypothesis. Of course, this simple model cannot explain the complex reality driving the income-consumption dynamics, however it gives an intuition in how to interpret short-run coefficients typically estimated in empirical work (see, e.g., Campbell and Mankiw 1990, 1991).

This is the modified Matlab code based on Perez (2000) to simulate income and consumption in Fig. 10.9.

```
clear all;
T=70; %years in life
R=50; %working years
rho=0.1; %fraction of liquidity constrained households
y(1)=100; %initial total income
y1(1)=(1-rho)*y(1);
y2(1)=(rho)*y(1);
i1=2;
while i1<=T;
if i1<=R;
y(i1)=y(i1-1)+10+150*sin(i1);
y1(i1)=(1-rho)*y(i1);
y2(i1)=(rho)*y(i1);
else;
y(i1)=0;
y1(i1)=0;
y2(i1)=0;
end;
i1=i1+1;
end;
a(1)=0; %initial wealth
```

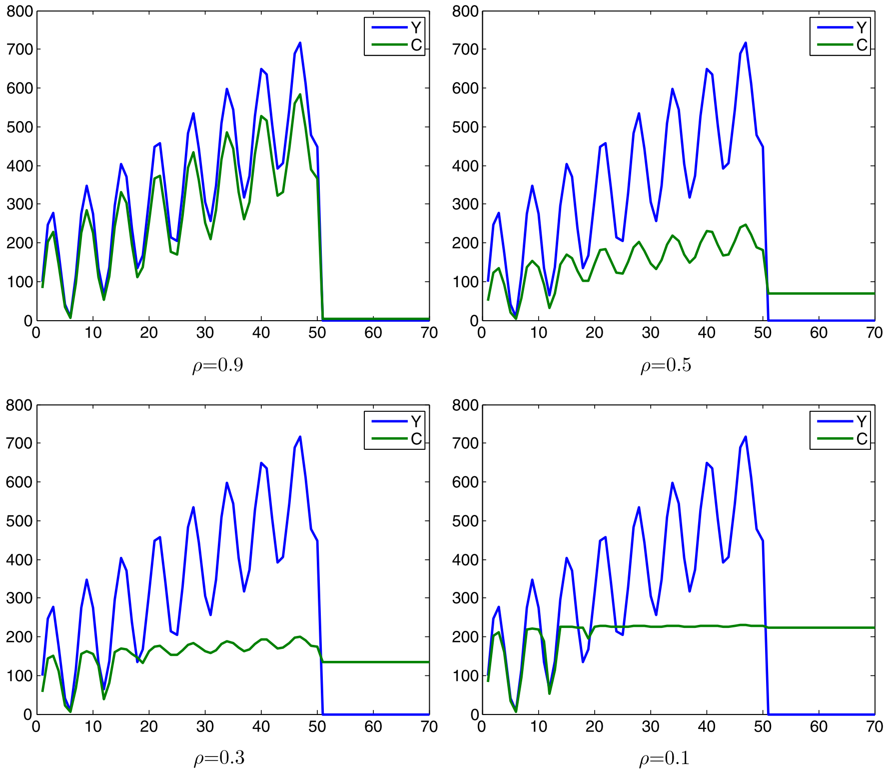

Fig. 10.9 Consumption volatility as a function of liquidity constraints

```
i1=1;
while i1<=T;
cstar(i1)=1/(T-i1+1)*(sum(y1(i1:T))+a(i1));
c1(i1)=max(0,min(cstar(i1),y1(i1)+a(i1)));
a(i1+1)=a(i1)+y1(i1)-c1(i1);
c2(i1)=max(0,y2(i1));
c(i1)=(1-rho)*c1(i1)+rho*c2(i1);
i1=i1+1;
end;
plot([y' c'])
```

Appendix B: Regression Results for the Auxiliary Income Equation the PIH Model

Table 10.16 Regression results, long-run coefficient and panel unit root tests for auxiliary income equation

	POLS	LSDV	AB-GMM	SYS-GMM	SYS-GMM	SYS-GMM	SYS-GMM
$Y_{i,t-1}$	0.98^{***}	0.96^{***}	0.96^{***}	0.94^{***}	0.86^{***}	1.16^{***}	1.26^{***}
	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)
$Y_{i,t-2}$						-0.19^{**}	-0.56
						(0.03)	(0.15)
$Y_{i,t-3}$							-0.26
							(0.18)
Constant	0.06^{***}	0.11^{***}		0.19	0.41	0.10^{***}	0.12^{**}
	(0.00)	(0.00)		(0.53)	(0.51)		
Trend					0.001		
					(0.67)		
LR-Coef.	0.98	0.96	0.96	0.94	0.86	0.97	0.96
Unit root	-11.62^{***}	-11.99^{***}	-12.52^{***}	-12.00^{***}	-10.81^{***}	-14.41^{***}	-15.76^{***}
(p-val.)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)

Note: POLS = Pooled OLS, LSDV = Least Square Dummy Variable Approach, AB-GMM = Arellano–Bond First Difference GMM, SYS-GMM = Blundell–Bond System GMM. LR-Coef. is the cumulated long-run coefficient. The Im et al. (2003) panel unit root test strongly rejects the null hypothesis of non-stationarity for the regression residuals

*Denote statistical significance at the 10% level **Denote statistical significance at the 5% level ***Denote statistical significance at the 1% level

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