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 $t = 3, \dots, T$ 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]

$$E(y_{i,t-\rho}\, \Delta u_{i,t}) = 0 \quad \text{for all } \rho = 2, \dots, t-1 \text{ and } t = 3, \dots, T. \tag{8.9}$$

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]

$$E(\Delta y_{i,t-1} u_{i,t}) = 0 \quad \text{for } t = 3, \ldots, T. \tag{8.12}$$

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 $t = 3, \ldots, T$ 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 $E(w_{i,1} \nu_{i,t}) = 0$.

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 $\hat{V}^S = \text{diag}(\sum_{i=1}^{N}\hat{u}_{i1}^2 Z_{i1}Z_{i1}', \dots, \sum_{i=1}^{N}\hat{u}_{iM}^2 Z_{iM} \times Z_{iM}')$, 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

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[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.

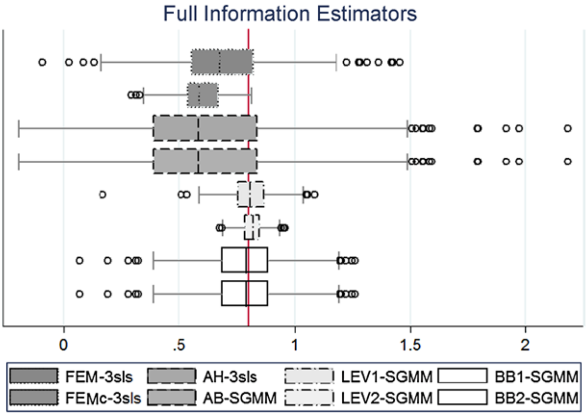


Fig. 8.1 $\hat{\alpha}_2$-simulation results with $N = 250$, $T = 5$, $\alpha_2 = 0.8$, $\xi = 1$

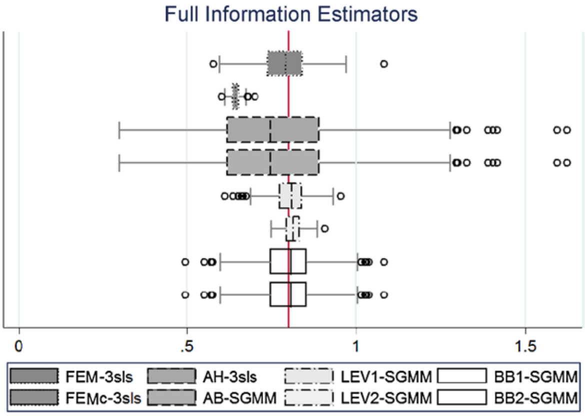


Fig. 8.2 $\hat{\alpha}_2$-simulation results with $N = 250$, $T = 15$, $\alpha_2 = 0.8$, $\xi = 1$

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 $N = 25$, $T = 15$, $\alpha_2 = 0.8$, $\xi = 1$

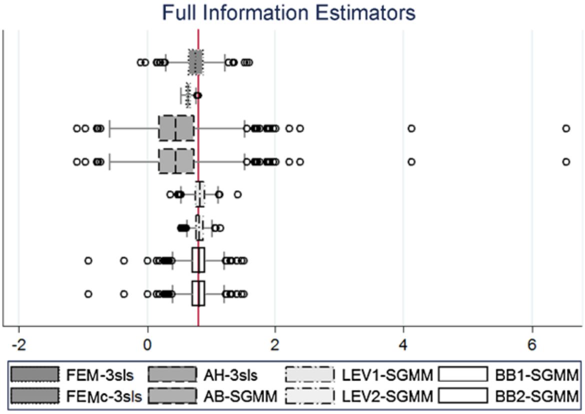
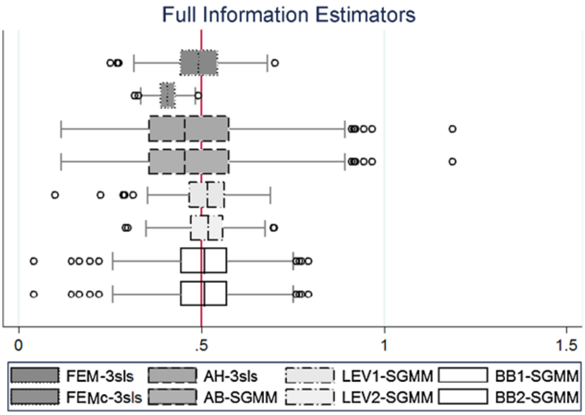


Fig. 8.4 $\hat{\alpha}_2$-simulation results with $N = 25$, $T = 15$, $\alpha_2 = 0.5$, $\xi = 1$



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.

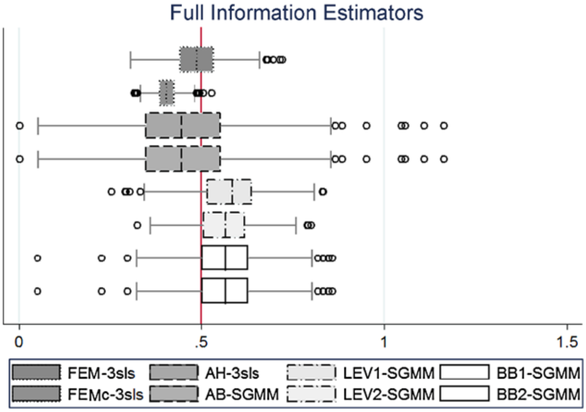


Fig. 8.5 $\hat{\alpha}_2$-simulation results with $N = 25$, $T = 15$, $\alpha_2 = 0.5$, $\xi = 4$

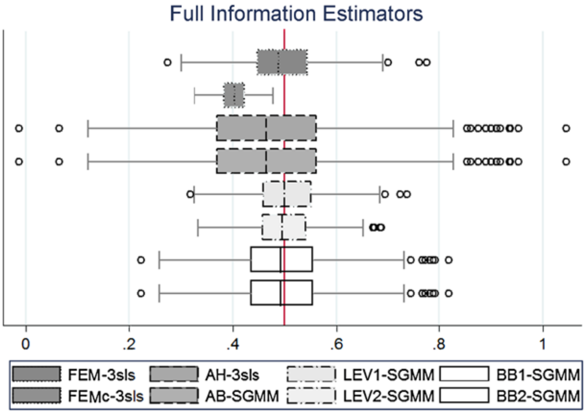


Fig. 8.6 $\hat{\alpha}_2$-simulation results with $N = 25$, $T = 15$, $\alpha_2 = 0.5$, $\xi = 0.5$

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 $P_i \in 1, \ldots, 16$

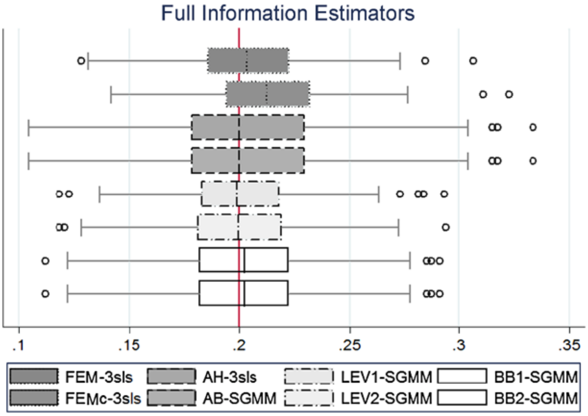


Fig. 8.7 $\hat{\alpha}_1$-simulation results with $N = 250$, $T = 15$, $\alpha_2 = 0.8$, $\xi = 1$

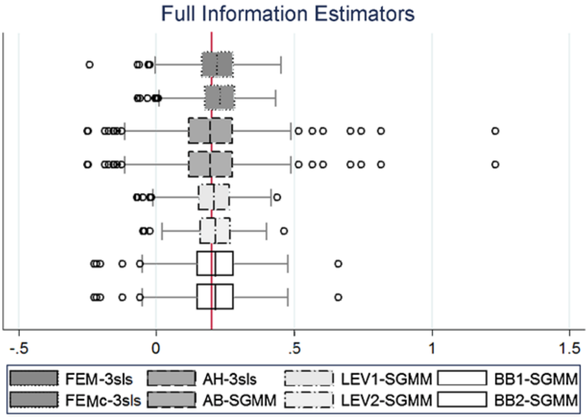


Fig. 8.8 $\hat{\alpha}_1$-simulation results with $N = 25$, $T = 15$, $\alpha_2 = 0.8$, $\xi = 1$

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

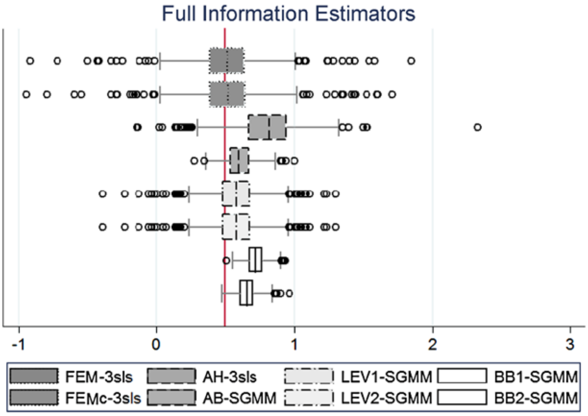


Fig. 8.9 $\hat{\beta}_1$-simulation results with $N = 25$, $T = 15$, $\alpha_2 = 0.8$, $\xi = 1$

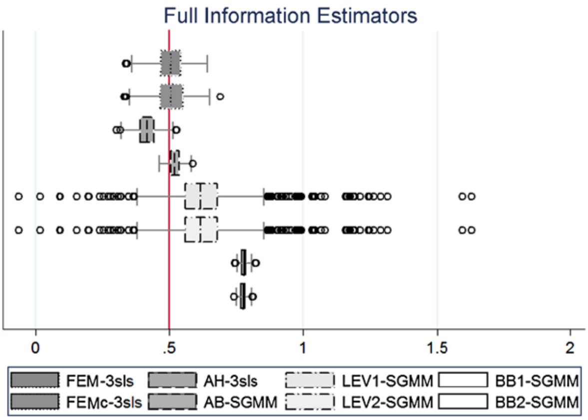


Fig. 8.10 $\hat{\beta}_1$-simulation results with $N = 250$, $T = 15$, $\alpha_2 = 0.8$, $\xi = 4$

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 $P_i \in 1, \ldots, 16$

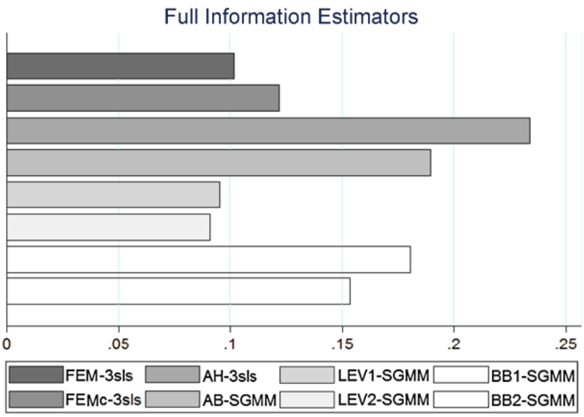


Fig. 8.11 NOMAD criterion for $N = 250$, $T = 10$, $\alpha_2 = 0.8$, $\xi = 1$

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).

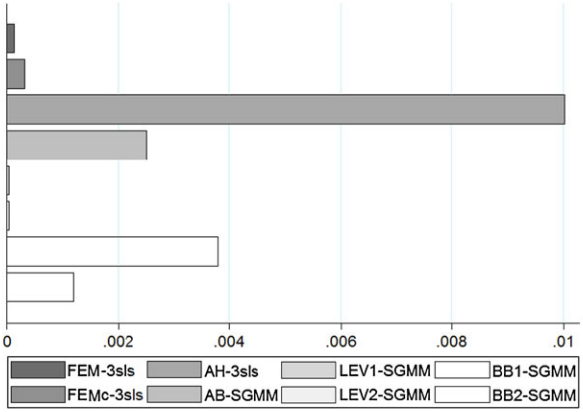


Fig. 8.12 NORMSQD criterion for $N = 250$, $T = 10$, $\alpha_2 = 0.8$, $\xi = 1$

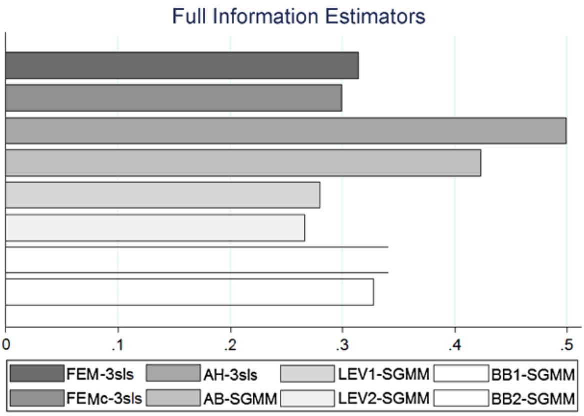


Fig. 8.13 NOMAD criterion for $N = 25$, $T = 10$, $\alpha_2 = 0.8$, $\xi = 1$

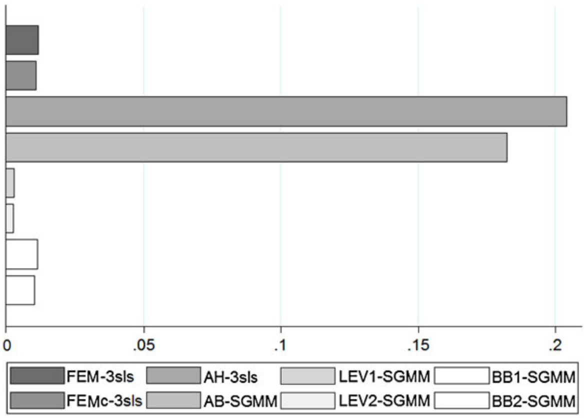


Fig. 8.14 NORMSQD criterion for $N = 25$, $T = 10$, $\alpha_2 = 0.8$, $\xi = 1$

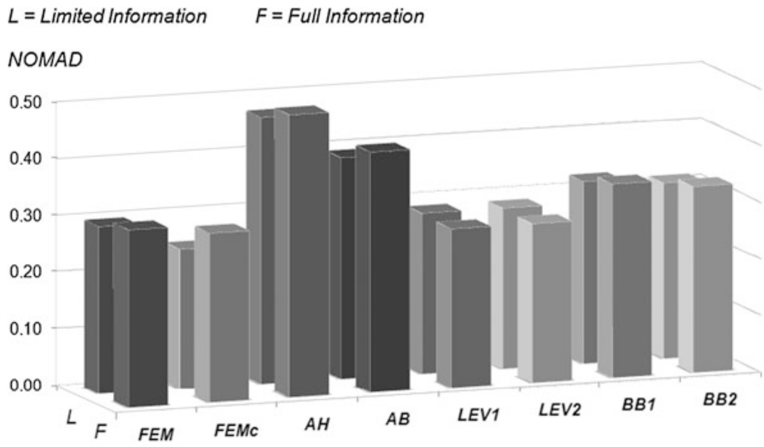


Fig. 8.15 NOMAD of full and limited information estimation for $N = 25$, $T = 10$

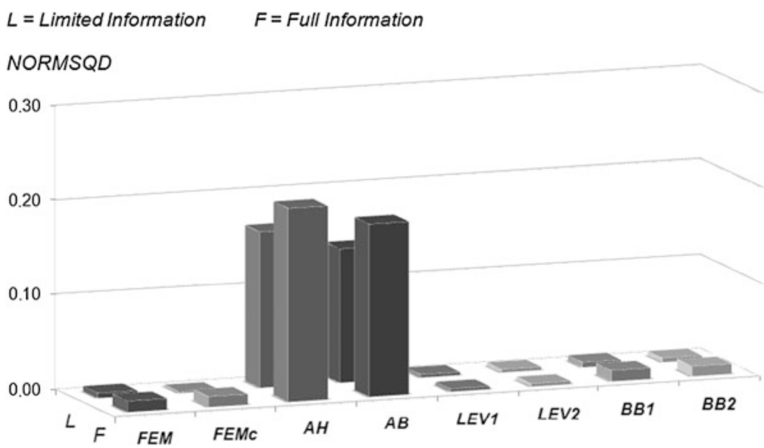


Fig. 8.16 NORMSQD of full and limited information estimation for $N = 25$, $T = 10$

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

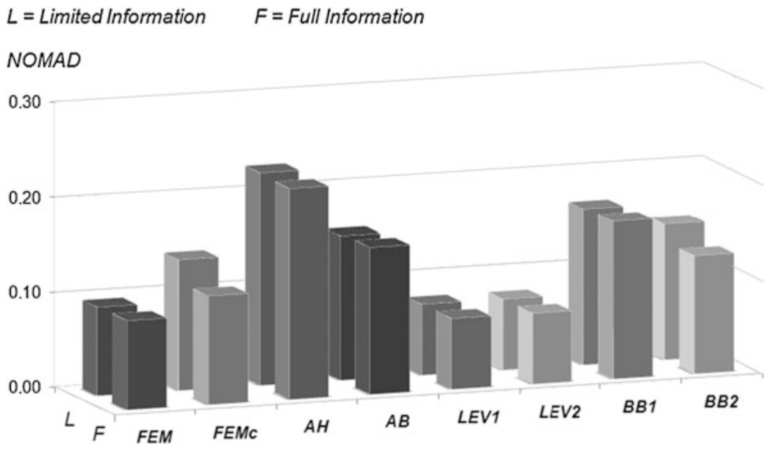


Fig. 8.17 NOMAD of full and limited information estimation for $N = 250$, $T = 10$

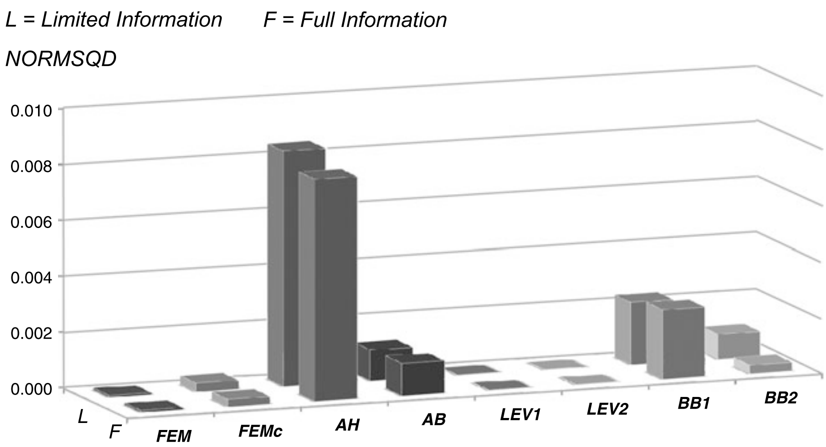


Fig. 8.18 NORMSQD of full and limited information estimation for $N = 250$, $T = 10$

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

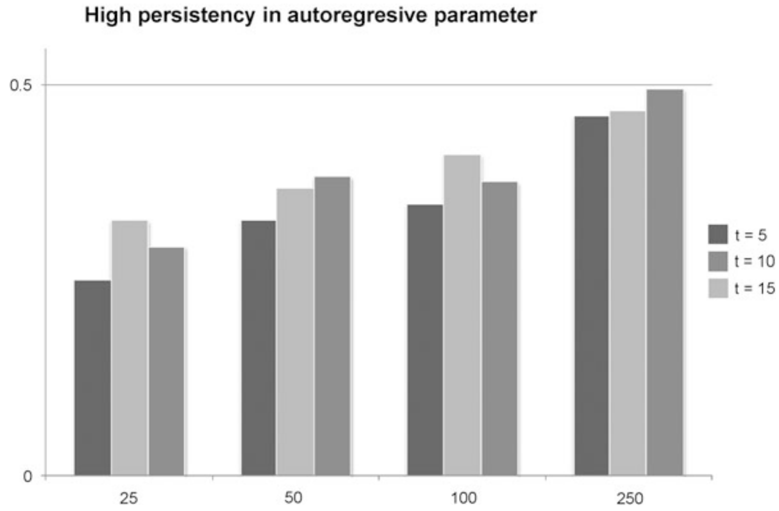


Fig. 8.19 Superiority of full and limited information estimation for $N \times T$ constellations with $\alpha_2 = 0.8$

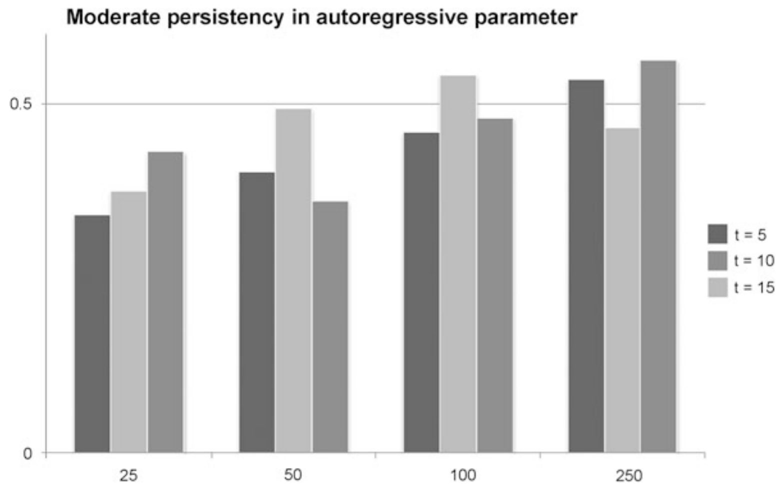


Fig. 8.20 Superiority of full and limited information estimation for $N \times T$ constellations with $\alpha_2 = 0.5$

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 $P_i \in 1, \ldots, 16$

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 $P_i \in 1, \dots, 16$

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 $i = 1, \dots, m$ 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).

[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.

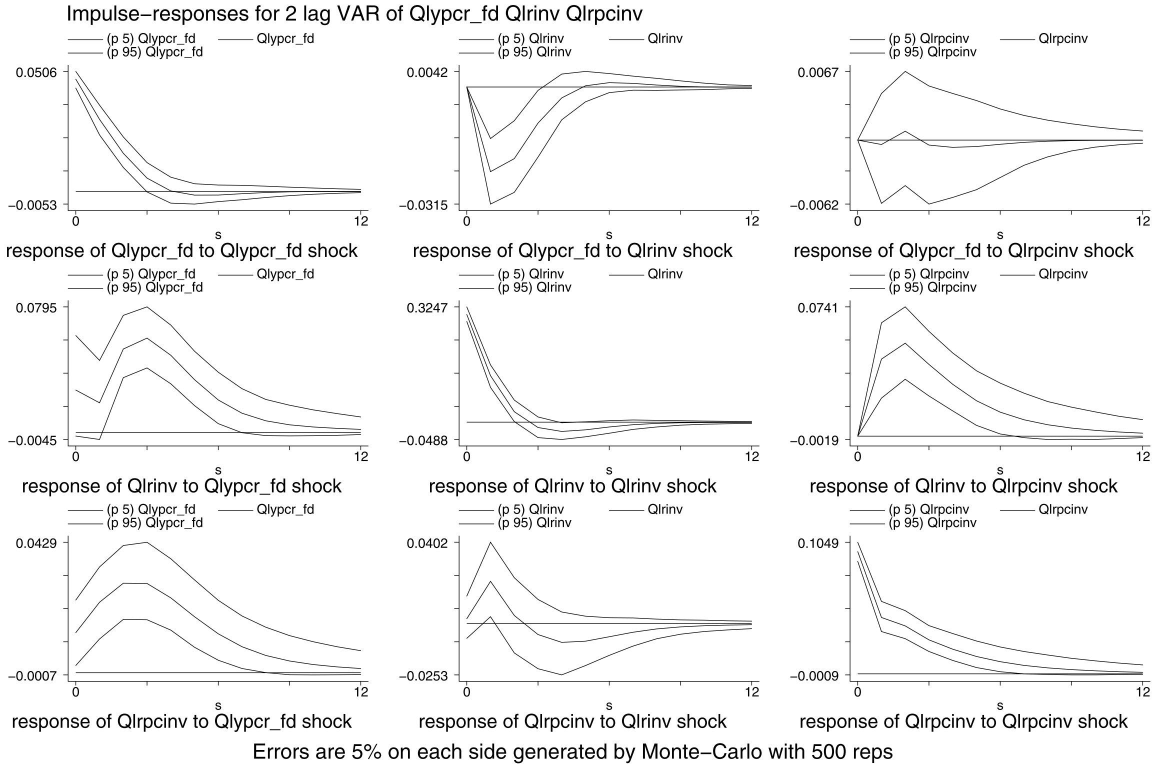


Fig. 8.21 Impulse–responses for PVAR(2) with $\Delta y_{i,t}$, $inv_{i,t}$ and $pub_{i,t}$. *Note*: With $\Delta y_{i,t} = Qlypcr\_fd$, $inv_{i,t} = Qlrinv$ and $pub_{i,t} = Qlrpcinv$

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.

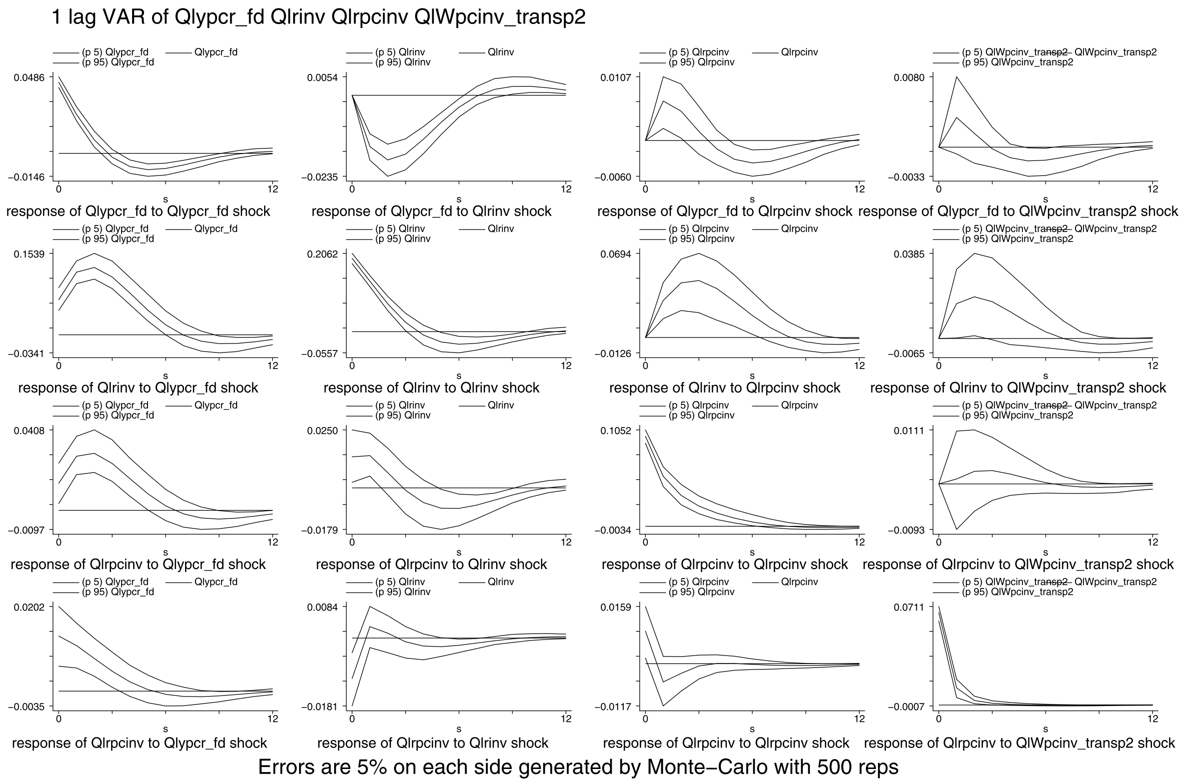


Fig. 8.22 Impulse–responses for PVAR(1) system with spillovers from transport infrastructure. *Note*: With $\Delta y_{i,t} = Qlypcr\_fd$, $inv_{i,t} = Qlrinv$ and $pub_{i,t} = Qlrpcinv$

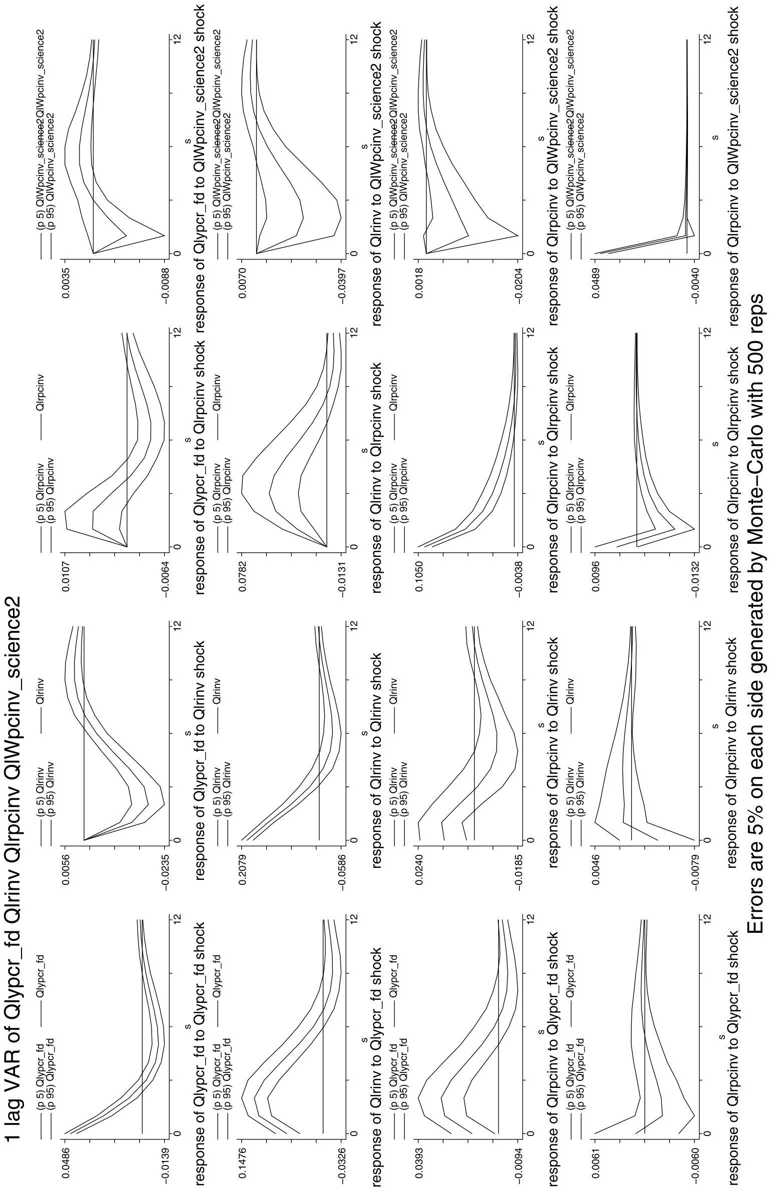


Fig. 8.23 Impulse–responses for PVAR(1) system with spillovers from science infrastructure. *Note:* With $\Delta y_{i,t} = Qlypcr\_fd$, $inv_{i,t} = Qlrinv$ and $pub_{i,t} = Qlrpcinv$

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-

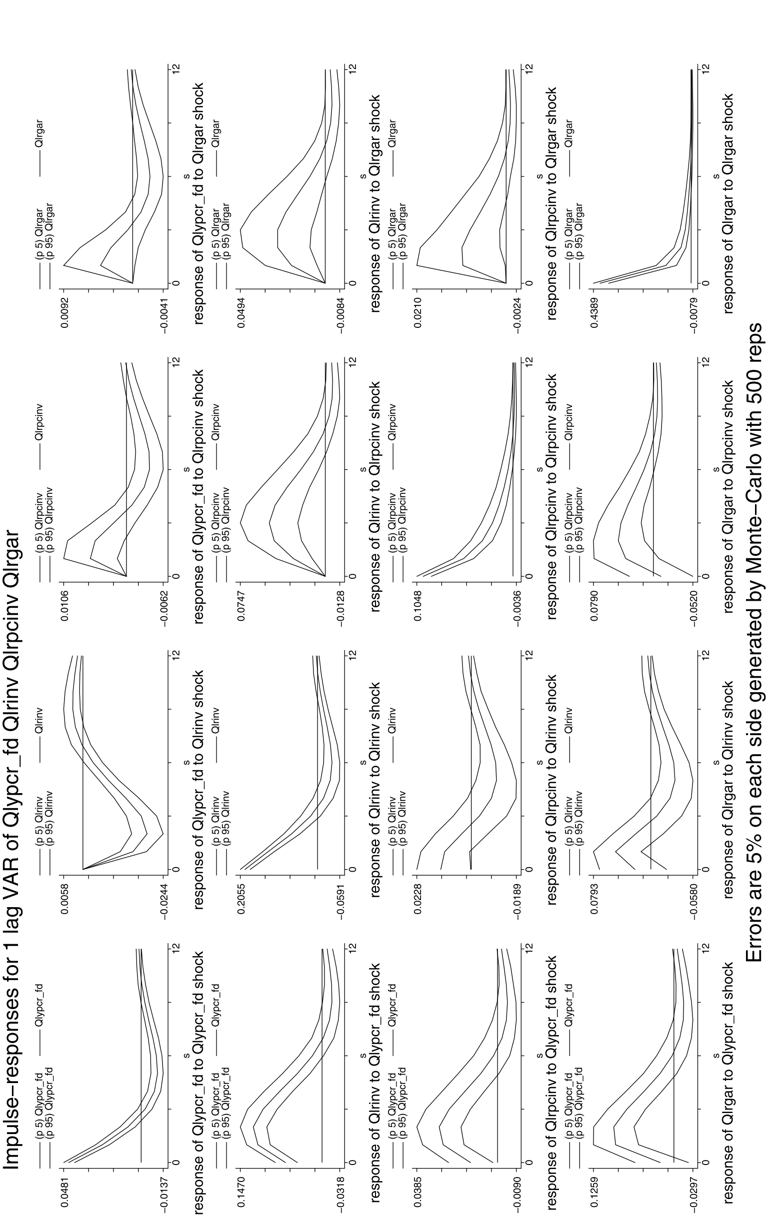


Fig. 8.24 Impulse–responses for PVAR(1) system with investment support grants (GRW). *Note*: With $\Delta y_{i,t} = Qlypcr\_fd$, $inv_{i,t} = Qlrinv$ and $pub_{i,t} = Qlrpcinv$

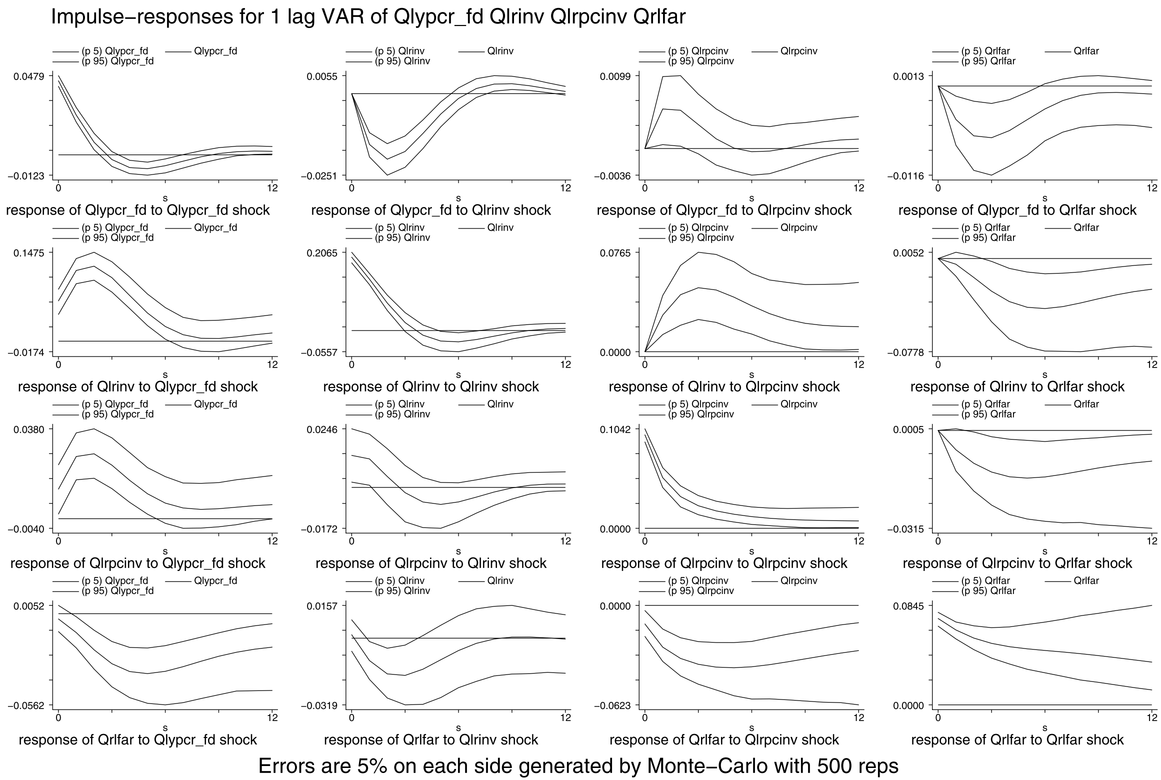


Fig. 8.25 Impulse–responses for PVAR(1) system with regional equalization payments (LFA). *Note*: With $\Delta y_{i,t} = Qlypcr\_fd$, $inv_{i,t} = Qlrinv$ and $pub_{i,t} = Qlrpcinv$

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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