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Intrasectoral structural change and aggregate productivity development: robust stochastic nonparametric frontier function estimates

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Abstract This paper investigates the sources of total factor productivity growth in the German manufacturing sector during 1981–1998. Decompositions of aggregate productivity growth are used to identify the effects of structural change and entry–exit on aggregate productivity growth. We find a substantial rise in productivity growth after the German reunification. The bulk of this rise can be attributed to structural change and entry–exit. Two methodological refinements are implemented. The first refinement is the application of robust stochastic nonparametric approaches to frontier function analysis, and the second is the calculation of bootstrap confidence intervals for the components of the productivity decompositions.

Keywords Productivity decomposition · Structural change · Manufacturing

JEL Classification D24 · O12 · L60

1 Introduction

Structural change within industries or sectors of an economy occurs because firms grow at different rates in terms of sales or employment. Industry structure also changes as a result of firms with sustained negative growth exiting from the industry and newly founded firms entering. This manifestation of the relative success of firms depends on their competitiveness, comprising their ability to offer attractive products on the markets to acceptable prices for the customers, in addition to their ability to adapt to changing market conditions or the capability to induce such changes via innovations.

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Thus, the differences in competitiveness should also be reflected in different levels of firm profitability as well as productivity. Both are of course closely related, and as Balk (2003) shows, total factor productivity change indeed measures the real component of profitability change. This perspective is also supported by Nickell (1996) and Nickell et al. (1997) with their finding of a positive relation between product market competition and total factor productivity growth.

Dynamic models of industry dynamics as presented by Ericson and Pakes (1995), Lambson (1991), Lentz and Mortensen (2005, 2008), Luttmer (2007), Nelson and Winter (1982) or Winter et al. (2000, 2003), among others, establish differential growth of firms as a result of differential success of their innovative activities which are reflected in differential changes of productivity. By that, the models are directly related to Schumpeter's (1942) notion of creative destruction and to the formal mechanism of replicator dynamics (see Metcalfe 1994). In a nutshell, this mechanism states that firms with above-average productivity levels tend to grow faster than firms with below-average productivity levels. This faster relative growth is expressed in terms of rising shares in either employment or sales, whereas slower relative growth is associated with shrinking shares. Thus, the replicator dynamics mechanism can be conceived as a reduced-form representation of the more elaborate models.

The present paper focuses on the investigation of the association of productivity change with differential growth of firms in terms of either employment or sales by means of productivity decomposition formulae. These formulae allow us to estimate the relevance of replicator dynamics for aggregate productivity growth of an industry or a broader sector. By that, the paper extents the study of Cantner and Krüger (2008) implementing two major methodological improvements. The first improvement consists of the application of the recently developed order-m and order-α approaches for robust stochastic nonparametric efficiency analysis. The second improvement is that bootstrap confidence intervals (CIs) are computed for the components of the productivity decomposition. Compared to the literature, the productivity decomposition formulae are not only used as a descriptive device to uncover the sources of aggregate productivity change (i.e., the contribution of structural change among the firms staying in the sector and the role entry and exit), but here estimation precision is also evaluated. Both methodological improvements lead to increased reliability of the findings and to a clearer identification of those effects which are really important and which can be estimated with precision.

The plan of the paper is to start by giving a short outline of the order-m and order-α approaches to productivity measurement in the following Sect. 2. This section also contains the description of the database. Then, two different decomposition formulae for aggregate productivity change are described in Sects. 3 and 4 together with a graphical presentation and a discussion of the corresponding results. Section 5 summarizes and concludes.

2 Productivity measurement and data

Total factor productivity is measured in many studies by traditional growth accounting or nonparametric data envelopment analysis (DEA) as used by Cantner and Krüger

(2008). In contrast, in this work the order-m and order-α approaches to robust stochastic nonparametric efficiency measurement are applied. The foundations of the order-m approach are developed in Cazals et al. (2002), while the approach has been made more accessible for practitioners by Daraio and Simar (2005, 2007). The quantile-based order-α approach is introduced by Aragon et al. (2005) and extended to the full multivariate case by Daouia and Simar (2007). Daraio and Simar (2007) as well as Simar and Wilson (2008) give thorough overviews over both approaches. As will become clear shortly, the robust approaches are able to combine the advantages of DEA and stochastic frontier analysis (SFA). They are both nonparametric (as DEA) and stochastic (as SFA). Being stochastic lets the approaches be robust since the frontier function is not forced to envelop all observations (including maybe outlying ones). Moreover, as nonparametric methods, the robust approaches have very favorable statistical properties.

2.1 Order-m

Starting point for the description of the order-m approach is the probabilistic definition of the technology set. Letting $\mathbf{x}$ denote the p-vector of inputs and $\mathbf{y}$ the q-vector of outputs of a decision-making unit (DMU), and letting capital letters indicate the corresponding random vectors, the probability of being dominated is simply given by $H_{XY}(\mathbf{x}, \mathbf{y}) = \Pr(\mathbf{X} \leq \mathbf{x}, \mathbf{Y} \geq \mathbf{y})$. This is the probability of observing a DMU using not more of each of the inputs than $\mathbf{x}$ to produce at least the output vector $\mathbf{y}$ (the inequality signs are taken to apply to each vector component separately). $H_{XY}(\mathbf{x}, \mathbf{y})$ can be decomposed as

$$H_{XY}(\mathbf{x}, \mathbf{y}) = \Pr(\mathbf{X} \leq \mathbf{x} | \mathbf{Y} \geq \mathbf{y}) \cdot \Pr(\mathbf{Y} \geq \mathbf{y}) = F_{X|Y}(\mathbf{x}|\mathbf{y}) \cdot S_Y(\mathbf{y})$$

and this is the conceptual basis for defining the input-oriented[1] radial efficiency measure

$$\theta(\mathbf{x}, \mathbf{y}) = \inf\{\theta : H_{XY}(\theta\mathbf{x}, \mathbf{y}) > 0\} = \inf\{\theta : F_{X|Y}(\theta\mathbf{x}|\mathbf{y}) > 0\}$$

in this stochastic framework, supposing $S_Y(\mathbf{y}) > 0$ whenever used. As a radial efficiency measure, $\theta(\mathbf{x}, \mathbf{y})$ gives the largest possible proportional reduction in all inputs so that the resulting input–output combination remains possible to realize while being dominated with a probability marginally larger than zero. This defines the attainable set of inputs for a given output level. For a sample of real data, this efficiency measure could be computed in principle by estimating $F_{X|Y}(\mathbf{x}|\mathbf{y})$ by the corresponding empirical distribution function.

The order-m approach takes as a benchmark for the productivity measurement of a DMU "the average of the minimal value of inputs for m units randomly drawn according to $F_{X|Y}(\cdot|\mathbf{y})$" (Daraio and Simar 2007, p. 16). This amounts to taking a

[1] Input orientation is favored here over output orientation because our DMUs are firms which are more likely to be able to decide about their input usage while being more constrained on the output side.

specific number m of randomly drawn DMUs from the sample to estimate the efficiency of the DMU under evaluation. These m reference DMUs are required to produce at least the output quantities of the DMU under evaluation and are used to determine the *partial* technology set

$$\Psi_m(\mathbf{y}) = \{(\mathbf{x}, \mathbf{y}') \in R_+^{p+q} : \mathbf{x}_j \leq \mathbf{x}, \mathbf{y}' \geq \mathbf{y}, j = 1, \ldots, m\}.$$

This set is called a partial technology set because it is constructed only from the m reference DMUs instead of the whole sample. The partial technology set is used to define the input-oriented radial efficiency measure by $\tilde{\theta}_m(\mathbf{x}, \mathbf{y}) = \inf\{\theta : (\theta\mathbf{x}, \mathbf{y}) \in \Psi_m(\mathbf{y})\}$. The order-$m$ efficiency measure is simply the expected value with respect to the distribution $F_{X|Y}(\mathbf{x}|\mathbf{y})$, i.e., $\theta_m(\mathbf{x}, \mathbf{y}) = E_{X|Y}(\tilde{\theta}_m(\mathbf{x}, \mathbf{y})|\mathbf{Y} \geq \mathbf{y})$.

The actual computation of the order-m efficiency measure can be implemented conveniently by a Monte Carlo algorithm. For a sample of n DMUs with input–output combinations $(\mathbf{x}_i, \mathbf{y}_i), i = 1, \ldots, n$ the algorithm requires the execution of the following steps: For any chosen DMU i under investigation with output vector $\mathbf{y}_i$, draw $m\,(<n)$ DMUs $(\mathbf{x}_j, \mathbf{y}_j), j = 1, \ldots, m$ from the sample with $\mathbf{y}_j \geq \mathbf{y}_i$ and compute the nonparametric efficiency measure against this technology set. Denote the result by $\hat{\theta}_m^b$. Repeating these steps B times results in B different efficiency measures $\hat{\theta}_m^1, \ldots, \hat{\theta}_m^B$ from which the order-m efficiency measure of DMU i is finally computed as the simple mean $\hat{\theta}_m = B^{-1} \cdot \sum_{b=1}^{B} \hat{\theta}_m^b$.

Daraio and Simar (2007) explain in detail how the single efficiency measure $\hat{\theta}_m^b$ against the partial technology frontier can be computed by nonparametric techniques, most notably DEA or free disposal hull (FDH). Typical default values for m and B used in practice are $m = 25$ and $B = 200$ (Daraio and Simar 2007), although a larger number of Monte–Carlo replications are preferred in the application here. Experimentation with different values showed that the results actually are very robust with respect to different choices for m, so we choose $m = 50$ and $B = 1{,}000$. All computations of the order-m estimates are performed using the package "FEAR" for R, supplied by Paul Wilson on his web page and documented in Wilson (2008).

The order-m efficiency measure has very appealing statistical properties. Since the efficiency of each DMU is evaluated repeatedly against a partial technology frontier spanned by just m of the sample DMUs, it is not required that the entire sample has to be enveloped by the frontier function. This fact gives the procedure its robustness, while preserving the nonparametric nature of the efficiency measurement. As Cazals et al. (2002) have shown, the order-m efficiency measure is a consistent estimator and converges at the usual (parametric) rate of $n^{1/2}$ irrespective of the number of inputs and outputs. This is rather exceptional for a nonparametric estimator where the rate of convergence usually declines with the dimensionality (here the number of outputs and inputs $p+q$) of the problem—the so-called curse of dimensionality. Thus, the order-m approach combines the advantages of nonparametric efficiency measurement methods such as DEA or FDH and the statistical properties of SFA. Order-m efficiency measures are nonparametric in that they require neither the specification of a functional form of the production function nor the specification of the distribution of the inefficiency term. At the same time, they are stochastic with the virtues of robustness and rapid convergence to the asymptotic magnitudes.

2.2 Order-α

While the order-m approach evaluates productivity by a repeated comparison to a partial frontier function, the order-α approach is based on the definition of the production frontier as a quantile. This also allows to have DMUs above of the estimated frontier function, which gives the approach its robustness properties. Similar to the order-m approach, the order-α approach is based on the same stochastic definition of the technology set specified by the probability of being dominated $H_{XY}(\mathbf{x}, \mathbf{y}) = \Pr(\mathbf{X} \leq \mathbf{x}, \mathbf{Y} \geq \mathbf{y})$.

The input-oriented radial efficiency measure of order-α, where $\alpha \in (0, 1]$, is defined as

$$\theta_\alpha(\mathbf{x}, \mathbf{y}) = \inf\{\theta : H_{XY}(\theta\mathbf{x}, \mathbf{y}) > 1 - \alpha\} = \inf\{\theta : F_{X|Y}(\theta\mathbf{x}|\mathbf{y}) > 1 - \alpha\}.$$

This efficiency measure is interpreted as the proportional reduction (if $\theta_\alpha < 1$) or increase (if $\theta_\alpha > 1$) of all inputs such that the DMU under investigation is dominated with probability $1 - \alpha$ by DMUs which are producing no less output. The choice of α is arbitrary and usually within the interval [0.90, 0.99]. Note that in the case $\alpha = 1$ we are back at the usual definition of the frontier function as a function enveloping all observations. In a sense the interpretation of α is analogous to the probability of committing a type-I error in statistical hypothesis testing. By a choice of $\alpha = 0.95$ 5 % of the DMUs use less of the inputs to produce no less output. Thus, we falsely classify a DMU as efficient in 5 % of the cases. With this interpretation, we can base our choice of $1 - \alpha$ on the usual significance levels employed in statistical hypothesis testing, e.g. 0.05.

Statistical properties of the order-α efficiency measure for the general multiple-input, multiple-output case are derived by Daouia and Simar (2007). They show that the order-α efficiency measure is a strongly consistent estimator and converges at the usual parametric rate $n^{1/2}$ to a normally distributed random variable. Moreover, they show that the efficiency measures calculated by the order-α approach have a bounded influence function,[2] whereas order-m efficiency measures have an unbounded influence function and therefore are less robust.

The actual computation of the order-α efficiency measures is based on the plug-in principle. Accordingly, a nonparametric estimate $\hat{F}_{X|Y}(\mathbf{x}|\mathbf{y})$ is simply substituted into the distance function defined above, leading to the empirical counterpart

$$\hat{\theta}_\alpha(\mathbf{x}, \mathbf{y}) = \inf\{\theta : \hat{F}_{X|Y}(\theta\mathbf{x}|\mathbf{y}) > 1 - \alpha\}.$$

[2] The influence function of an estimator, introduced by Hampel (1974), shows the effect of a small (tending to zero) fraction of outlying observations. If the influence function is unbounded, a small fraction of outlying observations is sufficient to let the estimator diverge. Estimators with an unbounded influence function are thus not robust. In contrast, estimators with a bounded influence function are considered to be robust.

An exact computational algorithm is provided by Daouia and Simar (2007, p. 381). This algorithm is readily available through its implementation in the R-package "FEAR" (Wilson 2008). In this paper we use this implementation with the input-oriented efficiency measure and fixed at $\alpha = 0.95$. Similar results are obtained for the choices $\alpha = 0.90$ and $\alpha = 0.99$.

2.3 Database

In the following the order-m and order-α approaches are used to estimate the all-time-best frontier functions based on the observations of a sample of 874 German manufacturing firms[3] existing between 1981 and 1998. These firms pertain to 11 industries at a roughly two-digit (SIC) level of aggregation. The specific industries considered are construction, food and beverages, textiles and apparel, paper and printing, chemicals and petroleum, rubber and plastics, metal products, machinery and equipment, electronics, transportation equipment and instruments.

The primary data sources are the balance sheets and the profit and loss accounts of the firms, assembled from the Hoppenstedt firm database, a commercial firm information service in Germany. In this database, information is available at the firm level but not for individual establishments of multiunit firms. For entering and exiting firms, only a part of the entire time span is observed. For each time period considered, an entry is recorded if a firm is not in the database at the start but is in the database at the end. Likewise, an exit is recorded if a firm is in the database at the start of the respective time period but is no longer present at the end.[4] This data set is also analyzed in Cantner and Krüger (2008) where additional descriptive statistics can be found.

The sample is somewhat selective and consists of mostly large quoted firms, predominantly with headquarters in the western part of Germany both before and after the reunification. Admittedly, small firms are generally omitted. However, it is reassuring to observe that the productivity effects of structural change, entry and exit are of a similar pattern and of a comparable magnitude as for more comprehensive data sets including small firms or based on establishments. To gain a feeling for the sample and the differences across the two subperiods considered later, the number of continuing as well as entering and exiting firms in the entire sample period (1981–1998) and the two subperiods (before 1981–1989 and after 1990–1998 the German reunification) is shown in Table 1.

In the first subperiod, the number of continuing firms is larger in all industries. Also, entry is more prevalent than exit in most industries during the first subperiod. Turbulence in terms of entry and exit is much more prevalent in the second subperiod,

[3] These firms are the DMUs referred to in the methodological description.

[4] Thus, entry as appearance in the data set may be de novo entry or may be due to firms growing to a size so that they become recognized by Hoppenstedt and the annual accounts will be recorded in the data set. Exit as disappearance from the data set may be real exit, or it may be the exit due to mergers or acquisitions by other firms. This should also be kept in mind when interpreting the entry and exit components of the productivity decomposition below. So, the effects of entry and exit on aggregate productivity growth are actually caused by a mixture of de novo entry, entry into the data set, real exit and exit due to mergers or acquisitions, respectively.

Table 1 Numbers of continuing, entering and exiting firms by industry

Industry	1981–1998			1981–1989			1990–1998		
	Cont.	Entry	Exit	Cont.	Entry	Exit	Cont.	Entry	Exit
Construction	14	15	10	21	5	3	17	12	8
Food and beverages	34	20	20	53	9	1	42	12	24
Textiles and apparel	20	6	21	37	8	4	24	2	21
Paper and printing	4	15	8	11	9	1	8	11	11
Chemicals and petroleum	19	32	29	47	15	1	26	25	38
Rubber and plastics	8	4	7	13	0	2	8	4	5
Metal products	24	22	16	38	14	2	29	17	27
Machinery and equipment	31	53	39	61	30	9	45	39	45
Electronics	10	30	17	26	22	1	23	17	23
Transportation equipment	8	19	8	16	11	0	16	11	17
Instruments	7	5	7	11	4	3	8	4	7

i.e., there are more firms entering in the second subperiod and also more firms exiting. Because this development occurs in all industries in a similar way, it is illuminating to have a look at the business cycle conditions during the period of interest. The German economy actually was in a recession at the beginning of the 1980s, and the first subperiod contains the trough of this recession and much of the prolonged recovery thereafter. The second subperiod contains the recession at the beginning of the 1990s, which was followed by a phase of sustained comparably low growth rates.

Using this database, we take as the single output variable the total sales from the profit and loss accounts, corrected for inventory changes and internally used firm services. Foster et al. (2008) raise concerns about productivity measures with revenue (sales) used as the output variable. Such revenue-based measures may be misleading in the presence of market power, which allows firms to raise prices above the industry average used for deflation. However, revenue-based measures also have the advantage of reflecting the effects of product innovations which are associated with price variation across firms (Syverson 2011, p. 345). Thus, viewing productivity as a comprehensive measure of competitiveness of multiproduct firms, the revenue-based output measure also has distinct virtues.[5]

Three input variables are used where labor input is measured by the number of employees, capital input is measured by the book value of firms' assets from the balance sheets, and materials input is taken from the position raw materials and supply from the profit and loss accounts of the firms. Since productivity comparisons over time require real data, all variables in monetary units are converted to real magnitudes using industry-specific price deflators from the 60-Industry Database of the Groningen Growth and Development Centre (O'Mahony and van Ark 2003).

[5] For a firm-level analysis with large multiproduct firms in the sample, there is no choice anyway. Physical output measures are only an alternative for physically homogeneous outputs at the plant level if such data are available as in the cases selected by Foster et al. (2008).

We estimate productivity in the form of total factor productivity against the benchmark of industry-specific all-time-best frontier functions. It is computed as the order-m or order-α efficiency measure, i.e., either as $a_{it} = \hat{\theta}_m(\mathbf{x}_{it}, y_{it})$ or $a_{it} = \hat{\theta}_\alpha(\mathbf{x}_{it}, y_{it})$, where the input–output combination of firm i in period t is evaluated against the reference set of the firms in the same industry pooling all time periods together.

3 Decomposition of Foster, Haltiwanger and Krizan (FHK)

The device taken here for the assessment of the contribution of structural change to aggregate productivity growth is to construct a measure of aggregate productivity growth and then to decompose this measure into several additive terms, each with its own economic interpretation. With a_{it} denoting the productivity level of firm i in period t as defined in the previous section and s_{it} denoting the corresponding share of firm i in total employment or sales of the industry in period t, aggregate productivity growth based on the change of share-weighted average productivity can be expressed as

$$\Delta \bar{a}_t^s = \bar{a}_t^s - \bar{a}_{t-k}^s = \Sigma_{i \in C \cup N} s_{it} a_{it} - \Sigma_{i \in C \cup X} s_{it-k} a_{it-k},$$

where $\bar{a}_t^s = \Sigma_{i \in C \cup N} s_{it} a_{it}$ and $\bar{a}_{t-k}^s = \Sigma_{i \in C \cup X} s_{it-k} a_{it-k}$ denote the share-weighted average productivity levels of periods t and $t-k$ ($k > 0$), respectively.[6] The summations run over several disjoint sets with C representing the set of continuing firms, N the set of entering firms and X the set of exiting firms (of course, with a total sample of n firms we have $C \cup N \cup X = \{1, \ldots, n\}$). Continuing firms have positive shares in both periods t and $t-k$. Entry and exit is taken into account by the fact that $s_{it-k} = 0$ in the case of the entering firms (i.e., firms that are not recorded in the data set in period $t-k$ but are contained in the data set in period t) and $s_{it} = 0$ in the case of the exiting firms (i.e., firms that are contained in the data set in period $t-k$ but disappear until period t). With this notation, the percentage growth rate of aggregate productivity over the period $t-k$ to t can be expressed as $\frac{100}{k} \cdot \Delta \bar{a}_t^s / \bar{a}_{t-k}^s$.

The aggregate productivity growth of an industry is here decomposed using the formula proposed by Foster et al. (2001), which is an extension of an earlier formula of Baily et al. (1992) also accounting for the contributions of entering and exiting firms. Accordingly, $\Delta \bar{a}_t^s$ can be decomposed into

$$\begin{aligned}\Delta \bar{a}_t^s = &\sum_{i \in C} s_{it-k} \Delta a_{it} + \sum_{i \in C} \Delta s_{it} (a_{it-k} - \bar{a}_{t-k}^s) + \sum_{i \in C} \Delta s_{it} \Delta a_{it} \\ &+ \sum_{i \in N} s_{it} (a_{it} - \bar{a}_{t-k}^s) - \sum_{i \in X} s_{it-k} (a_{it-k} - \bar{a}_{t-k}^s),\end{aligned}$$

[6] Since our sample mostly consists of large quoted firms, the meaning of aggregate productivity may be problematic. Large firms, however, naturally have large shares and are thus dominating the share-weighted aggregate productivity measure. Therefore, we stick to the standard terminology speaking of aggregate productivity also in this case. In addition, it is reassuring that the main findings are similar to those found in studies for other countries working on the level of individual establishments.

where Δa_{it} and Δs_{it} are defined as $a_{it} - a_{it-k}$ and $s_{it} - s_{it-k}$, respectively.

The interpretation of this decomposition is straightforward: For the continuing firms, the first component is the sum of the share-weighted productivity changes within firms (the so-called *within* component). The second component is a share cross-term which is positive if firms with above-average (below-average) productivity also tend to increase (decrease) their shares (labeled as the *between* component). This is followed by a covariance-type term which is positive if firms with increasing (decreasing) productivity tend to gain (lose) in terms of shares (called the *covariance* component). The latter two terms summarize the effect of structural change on aggregate productivity growth among the continuing firms of the industry. While the between component relates share changes to deviations of the productivity levels from the average, the covariance component relates share changes to productivity changes. It is apparent that the between component corresponds to the effect of the replicator dynamics mechanism mentioned in the Introduction.

The final two terms of the formula represent the *entry* and *exit* components. They comprise the contributions of the entering and exiting firms to aggregate productivity growth. The contribution of an entering firm to aggregate productivity growth is positive if it has a productivity level in period t above the initial average (i.e., the average of period $t - k$), while the contribution of an exiting firm to aggregate productivity growth is positive if its productivity level in period $t - k$ is below the initial average. The entry and exit components summarize these contributions, weighted by s_{it} in the case of the entry component and by s_{it-k} in the case of the exit component.

For all components, it is important to note that these are sums over the observations of heterogeneous firms. Thus, the positive (or negative) sign of a component results from a dominance of the positive (or negative) contributions of a part of the sample firms over the opposite contributions of the remaining part of the sample. There is always the possibility that positive and negative contributions from individual firms may cancel out to a considerable extent.

The shares required for the aggregation are specified as the shares of the firms in either total employment or total sales. The results of the decomposition are reported in graphical form in the subsequent figures for the total sample of firms. Each component of the decomposition is shown as a light gray bar for the whole sample period 1981–1998 on the left, a red (or medium gray) bar for the first subperiod 1981–1989 before the German reunification in the middle and a blue (or dark gray) bar for the second subperiod 1990–1998 after the German reunification on the right.[7] Entry and exit components are collapsed into a joint net entry component. The separate consideration of these components is picked up in the next section. In the body of the paper, we report the results for the total sample, whereas the detailed industry results are relegated to the Appendix.

Reported together with each bar is a 95 % CI computed by bootstrapping of the decomposition formula. These CIs are depicted in the figure by two horizontal bars

[7] It is worth stressing at this point that the differences found in the subperiods before and after the German reunification cannot entirely be attributed to that event but are also influenced to a considerable extent by the differences in the macroeconomic conditions before and after the year 1990.

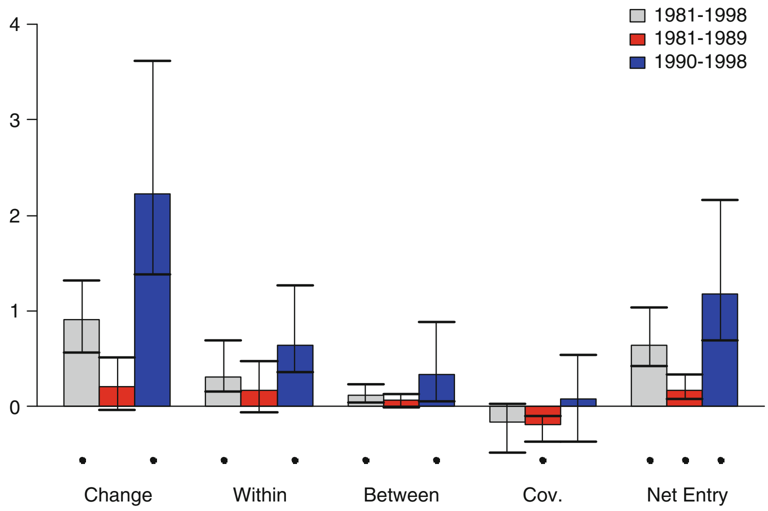

Fig. 1 FHK decomposition for order-m productivity estimates with employment shares

connected with a vertical line. They are computed as bias-corrected and accelerated (BC_a) CIs according to Efron (1987) and also explained in Efron and Tibshirani (1993, ch. 14). All bootstrap CIs are computed using the R-package "boot" accompanying the book of Davison and Hinkley (1997). They are based on 10,000 replications by drawing firms (with replacement) and arranging the pairs of the productivity levels and shares in period $t - k$ and t to a resample for which the decomposition formula is evaluated. In the case of entering and exiting firms, data for one of the periods are not available but are also not necessary to compute the respective components. If a dot is reported below a CI, then the zero value is not covered, and this indicates statistical significance. To the best of my knowledge, this is the first time that the estimation uncertainty associated with the components of a productivity decomposition exercise is assessed.

The first set of results using order-m productivity estimates with employment shares for aggregation is shown in Fig. 1. We observe statistically significant aggregate productivity growth for the entire sample period. This, however, appears to be mainly driven by the development during the second subperiod after 1990. Similarly, the literature reports widespread evidence of much larger productivity growth during the 1990s, compared to the period before 1990 for the majority of the European countries, the United States and Canada. Especially, the first half of the 1990s plays an important role for that outcome.

In the US discussion, the productivity gains of the 1990s are largely attributed to the effects of IT investments in IT-producing as well as in IT-using industries which show up with a delay (see Jorgenson et al. 2008; Oliner et al. 2007). van Ark et al. (2008) provide a deeper discussion of the differences between Europe and the United States and reasons underlying these developments.

For explaining these differences in productivity growth, the within component of course plays a role and is also statistically significant during the entire sample period and the second subperiod. Market selection, leading to structural change among the continuing firms as captured by the between and covariance components, is also significantly contributing to aggregate productivity change. This holds primarily for the between component which is positive and therefore supports the selection mechanism postulated by replicator dynamics.[8] Net entry contributes in a statistically significant and quantitatively important way to aggregate productivity growth during the entire sample period as well as during both subperiods. Here again, the effect is larger during the second subperiod compared to the first.

Although we are not interpreting the differences in the first and the second subperiod as the sole effects of the German reunification, there is an interesting relation to the literature on the impact of structural change on productivity growth in East European transition economies. This issue is assessed by Brown and Earle in a series of papers which are succinctly summarized in Brown and Earle (2008). These studies show that after the abolishment of central planning, the pattern of the decomposition is comparable to that of the United States and other countries and also to that of the present paper, whereas under the regime of central planning, reallocation was unrelated to productivity.[9]

The reasons for this pattern are, however, likely to be different for our sample of firms which are predominantly large German firms hosted in the western part. Many of the factors that are considered to be responsible for East European countries discussed in that literature (i.e., the type of privatization (domestic vs. foreign), the institutional setting and business environment, macroeconomic conditions, access to entrepreneurial knowledge and educated workers, labor market tensions, access to finance, the introduction of new technologies and managerial techniques, the extent of competition and the export orientation of the firms) are not equally important for our sample.

What is changing in Germany between the two subperiods and what can plausibly explain the differences before and after the reunification is the enlargement of the market leading to increasing output (which is fully measured by sales) and increased utilization of the inputs (which is only partly or not at all reflected in the labor and capital input measures). Both developments lead to a rise in measured productivity. In addition, as mentioned above, business cycle conditions are rather different in the two subperiods, with macroeconomic growth larger on average and more volatile in the second subperiod compared to the first.

The results with sales shares instead of employment shares are shown in Fig. 2. Some differences to the results with employment shares can be recognized, but the basic pattern appears robust and the essential aspects of the interpretation go through unmodified. The between component is not significant in any period when sales shares

[8] Recall that according to replicator dynamics, firms with above (below)-average productivity levels tend to have increasing (decreasing) employment shares.

[9] In the words of Brown and Earle (2008, p. 109): "Unlike under central planning, job reallocation during the transition has contributed significantly to aggregate productivity growth. Jobs have been reallocated from less to more productive incumbent firms, and the exiting firms have been predominantly less productive ones. Though entering firms have not initially been more productive than incumbents, the surviving ones have caught or surpassed incumbents within 3 years."

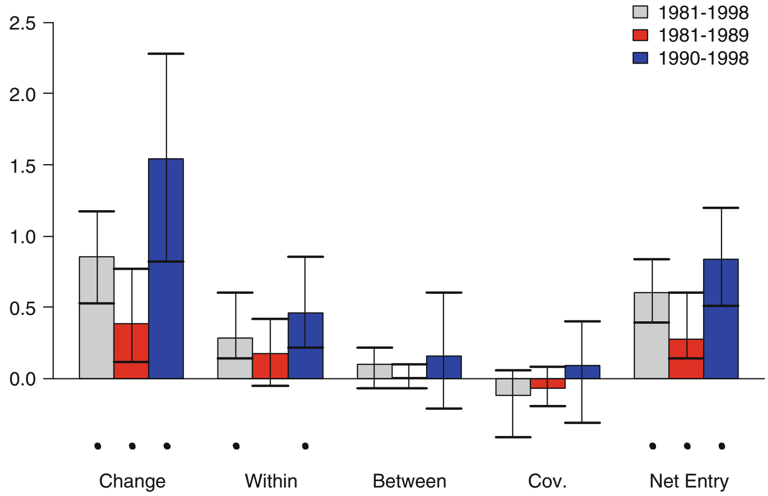

Fig. 2 FHK decomposition for order-m productivity estimates with sales shares

are used for the aggregation. The contribution of the net entry component to aggregate productivity growth remains considerable.

Taken together, aggregate productivity growth in the period after the German reunification is fuelled by the within component (with a contribution of about 30 %), the between component (about 20 %) and the net entry component (about 50 %), whereas the covariance component appears not to be overly important. This means that the components related to structural change are able to explain the majority of the aggregate productivity change during that period.

Turning to the corresponding order-α results with employment shares for the aggregation in Fig. 3, we can observe rather similar findings. The overall pattern and the

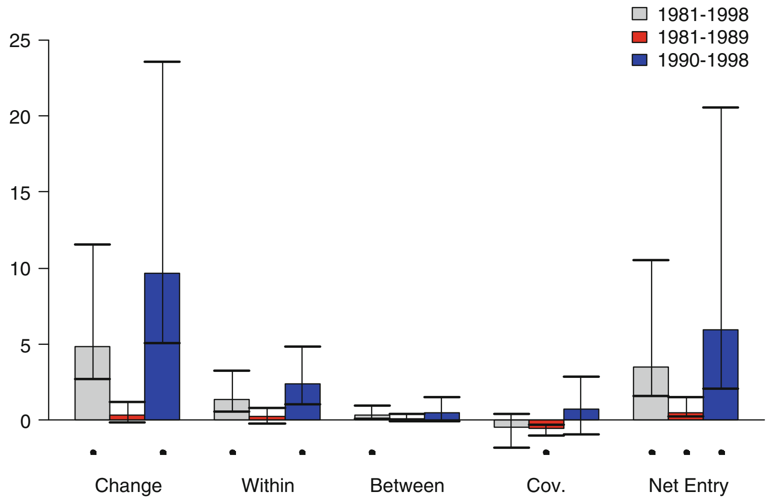

Fig. 3 FHK decomposition for order-α productivity estimates with employment shares

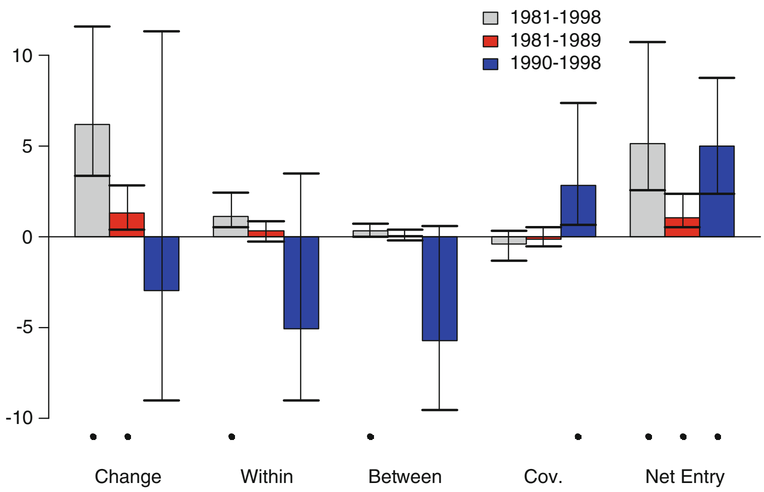

Fig. 4 FHK decomposition for order-α productivity estimates with sales shares

relative importance of the decomposition components appear to be robust to the choice of method. The magnitude of aggregate productivity change and the components is, however, substantially larger when the order-α approach is used. Compared to the productivity growth rates reported in the literature, the order-m approach leads to much more reasonable results.

In contrast, the order-α approach with sales shares depicted in Fig. 4 leads to rather different results that cannot be intuitively interpreted. The CIs are much wider here. The difference in the results obtained with the order-m and order-α approaches and the wider CIs can be explained by the better small-sample properties of the order-m approach. The recent Monte Carlo study of Krüger (2012) demonstrates the superior performance of order-m with respect to the mean absolute error and the rank correlation with the true efficiencies. Thus, the price to be paid for the greater robustness of the order-α approach seems to be a much greater deal of variability in small samples.

In the Appendix, analogous figures with the results for the eleven individual industries are reported. In each figure the respective total sample results are repeated in the upper left panel. Considering the order-m results by looking at the other plots in the first figure, the same basic pattern as for the total sample of firms can be observed in many cases. For some industries, however, the CIs appear to be rather wide due to the smaller number of observations. This is in particular the case for food and beverages, textiles and apparel, rubber and plastics as well as for metal products. Despite the wide CIs in these cases, the significant effects have the expected sign, thus supporting the overall conclusions for the other industries and the total sample. Structural change appears to be particularly important for chemicals and petroleum as well as instruments. For some industries the covariance component is negative (implying that productivity and share changes predominantly point to different directions) and sometimes also significantly so. Overall, the covariance component appears not to be very important quantitatively. In the case of the order-α approach, the results for the individual industries are more in line with the previous findings when using employment shares. Also with sales shares, the order-α industry results are not deviating as much from the general pattern as do the total sample results in this case.

4 Modified decomposition of Griliches and Regev (GR)

In this section, we turn to an alternative decomposition formula. This decomposition is due to Griliches and Regev (1995) and is considered to be more robust with respect to outliers in the data. A drawback of this formula is that the results are less straightforward to interpret. In addition, the covariance component is lost, but this does not seem to be overly important since that component was rather small in magnitude and frequently insignificant in the above results. Foster et al. (2008) provide a modified version of the Griliches–Regev formula, which is used subsequently in this paper. This formula decomposes the numerator of the aggregate productivity growth rate as follows:

$$\Delta \bar{a}_t^s = \sum_{i \in C} \bar{s}_i \Delta a_{it} + \sum_{i \in C} \Delta s_{it} (\bar{a}_i - \bar{a}^s) + \sum_{i \in N} s_{it} (a_{it} - \bar{a}^s) - \sum_{i \in X} s_{it-k} (a_{it-k} - \bar{a}^s),$$

with the above-introduced notation and additionally $\bar{a}_i = \frac{1}{2}(a_{it} + a_{it-k})$, $\bar{s}_i = \frac{1}{2}(s_{it} + s_{it-k})$ and $\bar{a}^s = \frac{1}{2}(\bar{a}_t^s + \bar{a}_{t-k}^s)$. The main difference to the formula of Foster et al. (2001) is that the effects are now based on the average productivities and shares ($\bar{a}_i$, $\bar{s}_i$ and $\bar{a}^s$), which makes the estimation more robust, and that the covariance effect is no longer present.

Analogous to the presentation of the results in the previous section, the order-m results with employment shares are reported in Fig. 5 and with sales shares in Fig. 6. The corresponding order-α results with employment and sales shares can be

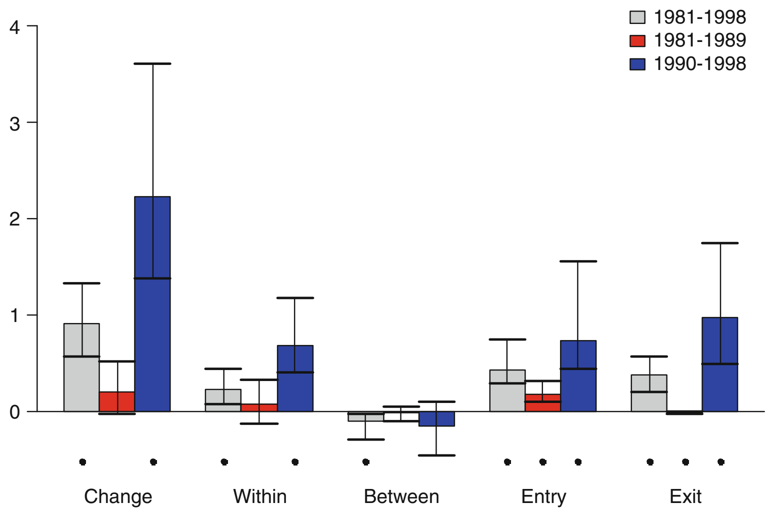

Fig. 5 GR decomposition for order-m productivity estimates with employment shares

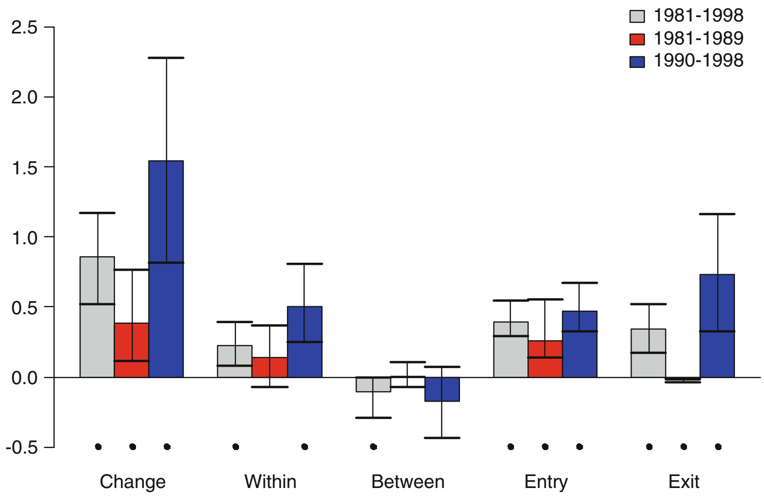

Fig. 6 GR decomposition for order-*m* productivity estimates with sales shares

found in Figs. 7 and 8, respectively. Again, the detailed industry results are in the Appendix. Now, the missing covariance component leaves the space to show the entry and exit components separately, thus completing the analysis of the previous section in this respect. Note that the entry and exit components are identical to those in the FHK decomposition formula so that we can now discuss the effects of entry and exit separately, which were previously combined in the joint net entry component. CIs are again computed as BC_a bootstrap CIs whenever possible. In two cases, rubber and plastics and transportation equipment during the first subperiod 1981–1989, this proved not to be possible[10] and bootstrap percentile intervals are reported instead.

From the figures it can be observed that the results are again very similar to those of the FHK decomposition for both methods to estimate productivity. This holds for the total sample as well as for the individual industries. The modified between component is now more frequently negative and sometimes significantly so. This finding should not prematurely be interpreted as evidence against selection according to the replicator mechanism since the between component is here different from the previous decomposition. In the modified Griliches–Regev formula, this component is no longer the deviation of the initial-period (period $t - k$) productivity level of firm i from the initial-period (share-weighted) average productivity level, which is multiplied with the share change. Instead, the difference is based on the averages of the actual and pervious period productivity levels. In the case of productivity growth, this tends to be larger than the previous period productivity level and may serve as an explanation for the weakened (and even negative) outcomes of the modified between component.

[10] The program terminated with an error message.

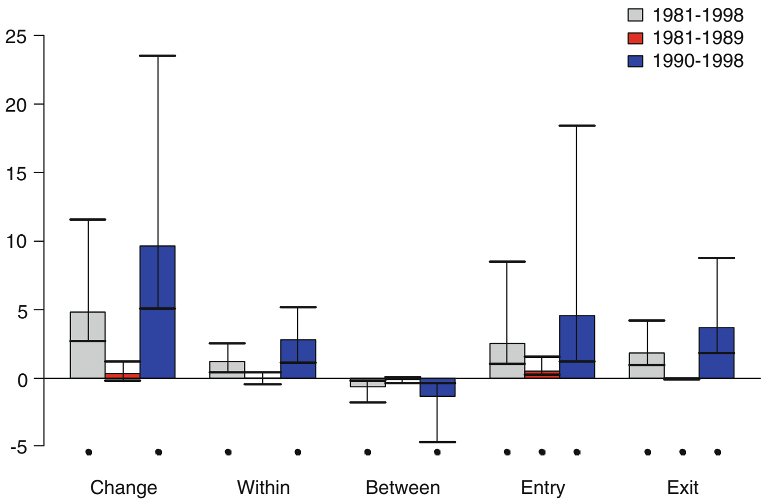

Fig. 7 GR decomposition for order-α productivity estimates with employment shares

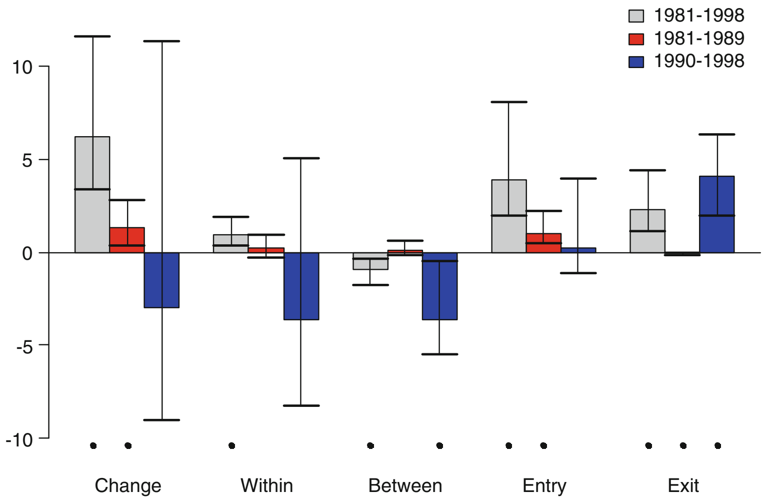

Fig. 8 GR decomposition for order-α productivity estimates with sales shares

Concerning the contributions of entry and exit, the results reveal that the large contribution of net entry is due to both the entry and the exit component. An explanation for the positive entry effect may be that entering firms are endowed with machinery and equipment of more recent vintages which are naturally associated with higher levels of productivity. A positive and statistically significant entry effect can be observed for the total sample as well as for most individual industries (see the Appendix) and time periods. As before, this finding applies likewise to the order-m and order-α approaches. Of course, on occasion certain effects are significant in one approach while being insignificant in the other, but the majority of the significances and the relative magnitudes of the effects is robust.

The findings with the modified Griliches–Regev decomposition are also robust to the utilization of sales shares instead of employment shares for the aggregation. Firms that are forced to exit especially in the second subperiod have productivity levels considerably below the average and thus contribute positively to aggregate productivity growth. As we observed in the discussion of the previous section, the results obtained with the order-α approach and sales shares are different from the corresponding order-m results for the total sample but are more in agreement for the individual industries.

5 Conclusion

Considered together, the results reported in this paper, generated with the recently developed robust stochastic nonparametric order-m and order-α approaches to frontier function analysis, give rise to several conclusions. First, aggregate productivity growth in German manufacturing was substantially higher in the years after the German reunification compared to the years before the German reunification. Second, regarding the sources, productivity growth within individual firms makes an important contribution, but structural change among the continuing firms can explain a considerable part as well. Third, also important is the contribution of entry into and exit from the sample, where especially entering firms predominantly have above-average productivity levels. Fourth, this pattern of results largely holds when all firms are pooled together irrespective of their industry assignment as well as for the majority of the individual industries considered.

These findings match results of Baldwin and Gu (2006) for Canada, Disney et al. (2003) for the UK and Foster et al. (2001) for the United States.[11] Note that these studies operate on the level of establishments, whereas the present study is on the level of firms. Baldwin and Gu (2011) note that their firm-level findings for Canadian manufacturing are consistent with their previous study on the establishment level. After the abandonment of central planning, a similar pattern of results is also found for firms in East European transition economies (Brown and Earle 2008). Baldwin and Gu (2011) also compare the manufacturing sector with retail trade finding a much larger contribution of the between component in retail trade than in manufacturing, where the within component is dominating. Entry and exit of firms is associated with a considerable contribution in both manufacturing and retail trade, with a larger contribution in retail. These results for Canada are consistent with the findings of Foster et al. (2006) for US retail trade.

With the methodological refinements implemented in this paper, the essential results of Cantner and Krüger (2008) for Germany can also be confirmed, although some effects appear to be attenuated when using the robust approach. This applies in particular to the covariance component. In addition to the application of the

[11] See also the survey articles by Bartelsman and Doms (2000) and Haltiwanger (2000). Krüger (2008) contains a review of the literature mostly concerned with intersectoral structural change.

robust order-m and order-α approaches, the second methodological refinement implemented in the present paper is the computation of CIs for the components of the productivity decompositions. Overall, the width of the CIs reveals that the results of productivity decompositions are frequently associated with substantial estimation uncertainty.

The significant role of structural change among manufacturing firms in shaping industry dynamics is also emphasized in the literature. Using a completely different methodological approach and calibration of parameters to the US economy, Luttmer (2007) finds about half of aggregate growth resulting from selection among firms. Selection there is associated with an excess of productivity growth of entrants over productivity growth of the incumbents. Lentz and Mortensen (2008) estimate a theoretical model based on Klette and Kortum (2004) by methods of indirect inference with Danish firm data. In this model more productive firms grow faster than less productive firms in the steady state. One central finding is there as well that structural change among existing firms and net entry account for the bulk of aggregate growth and productivity growth.

Unfortunately, the outcomes concerning the between effect capturing the force of market selection according to the replicator mechanism are not entirely conclusive. The same applies to the covariance effect capturing the association of share change with firm productivity growth. This is a further piece of evidence for the complex relation of technological performance (in a broad sense measured by productivity change) and the economic success or failure of firms. This relation is not only part of neoclassical economic thinking as is clear from reading the literature cited in the introduction. It is also a widespread observation in case studies concerned with industries and countries (see e.g., Steil et al. (2002) for a collection of those studies) and a central topic in evolutionary economics (see Dosi et al. (1997) for a selective review). Syverson (2011), in his recent survey of the empirical literature on the relation between the intensity of competition and productivity levels or growth rates, finds an overall positive relation. Of course, this issue is highly important and a more definite answer may be reached by ongoing research on this issue.

Acknowledgments I thank the participants of the 2009 EARIE conference in Toulouse, the 2010 DRUID Summer Conference in London and the Economic Seminar in Ottobeuren 2011 for their comments. I am also grateful to Uwe Cantner for generously providing the data. Of course, neither of them is responsible for the final outcome.

6 Appendix: Detailed industry results

See Figs. 9, 10, 11, 12, 13, 14, 15 and 16.

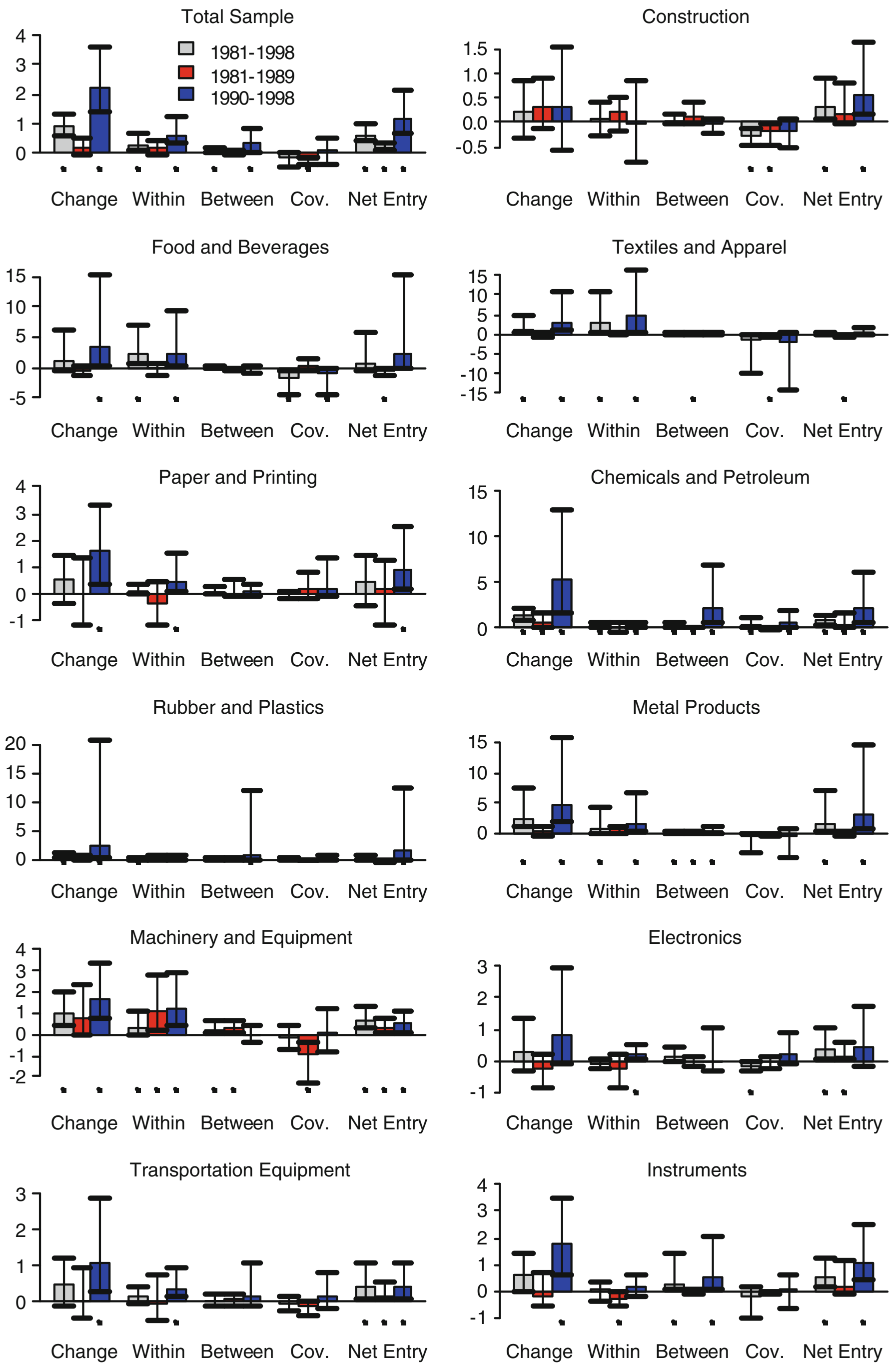

Fig. 9 FHK decomposition for order-m productivity estimates with employment shares

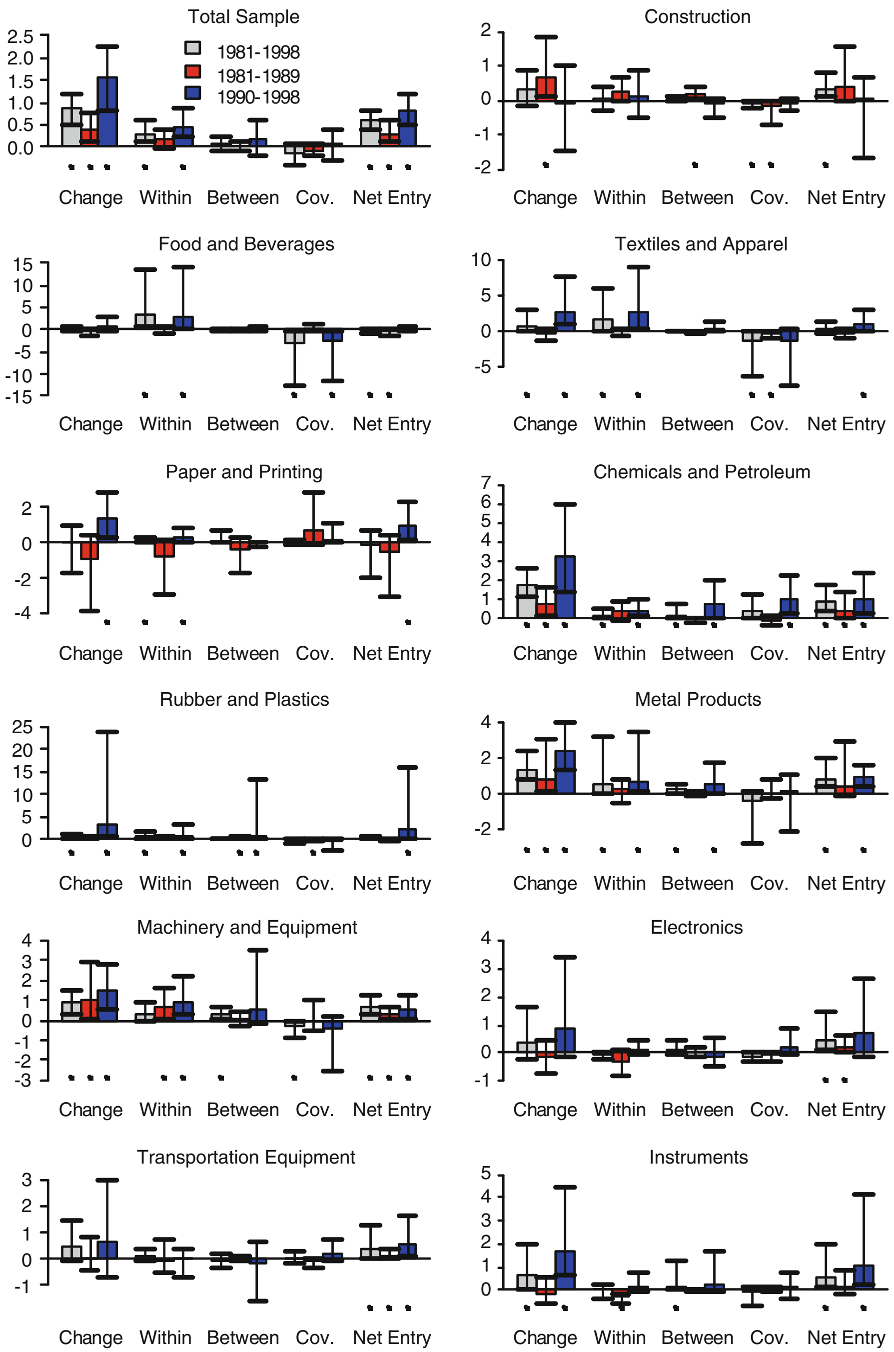

Fig. 10 FHK decomposition for order-m productivity estimates with sales shares

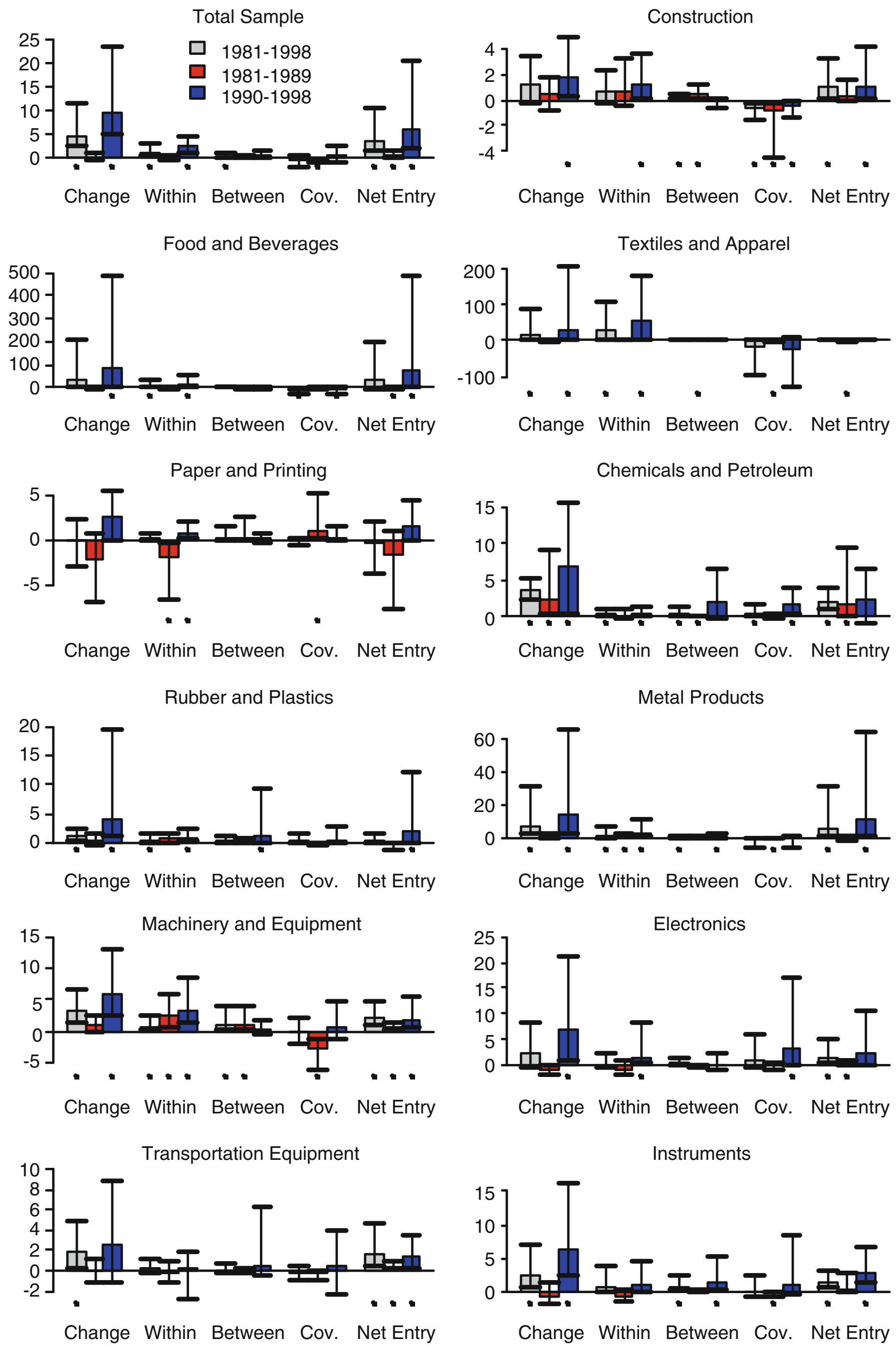

Fig. 11 FHK decomposition for order-α productivity estimates with employment shares

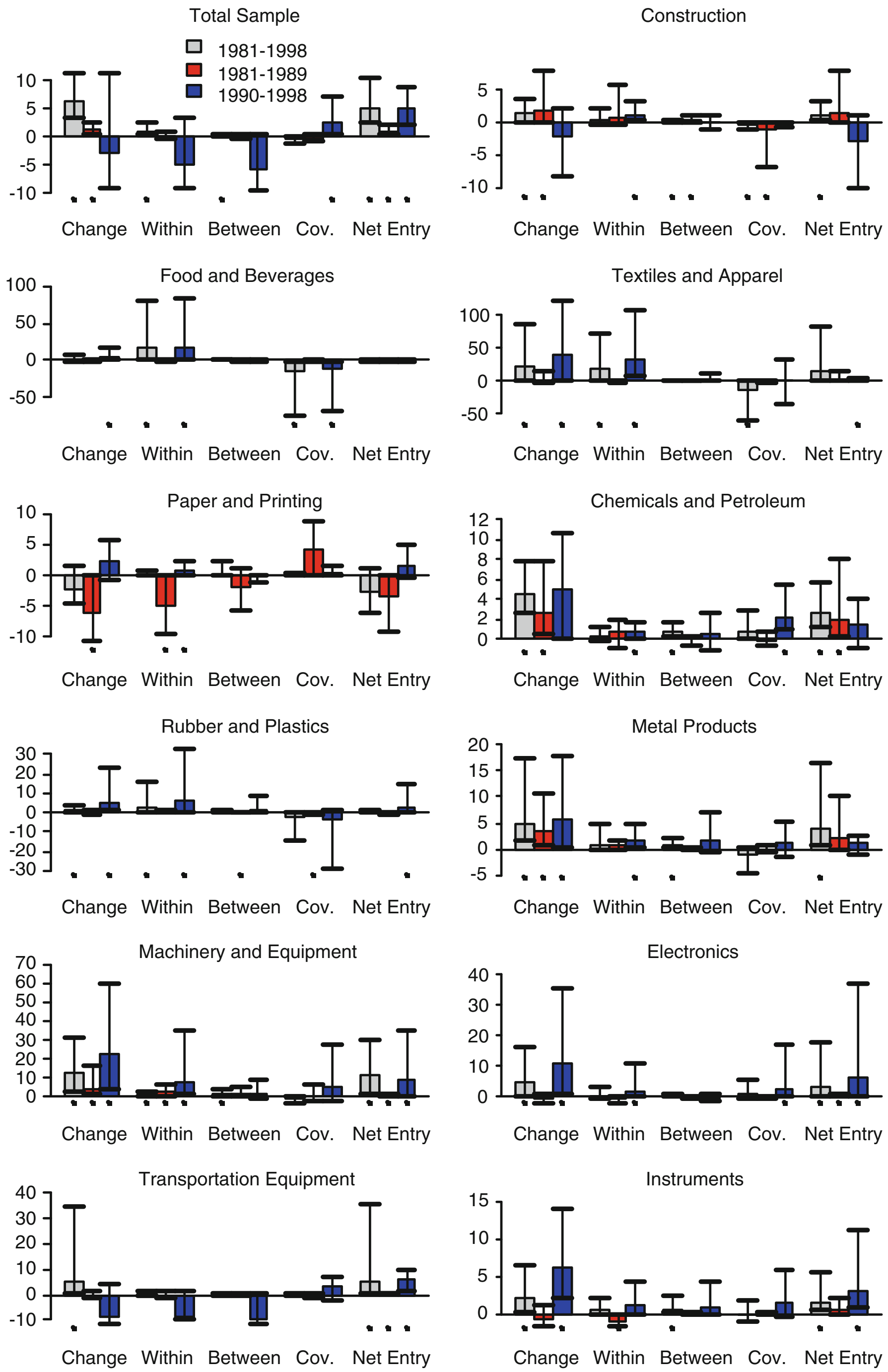

Fig. 12 FHK decomposition for order-α productivity estimates with sales shares

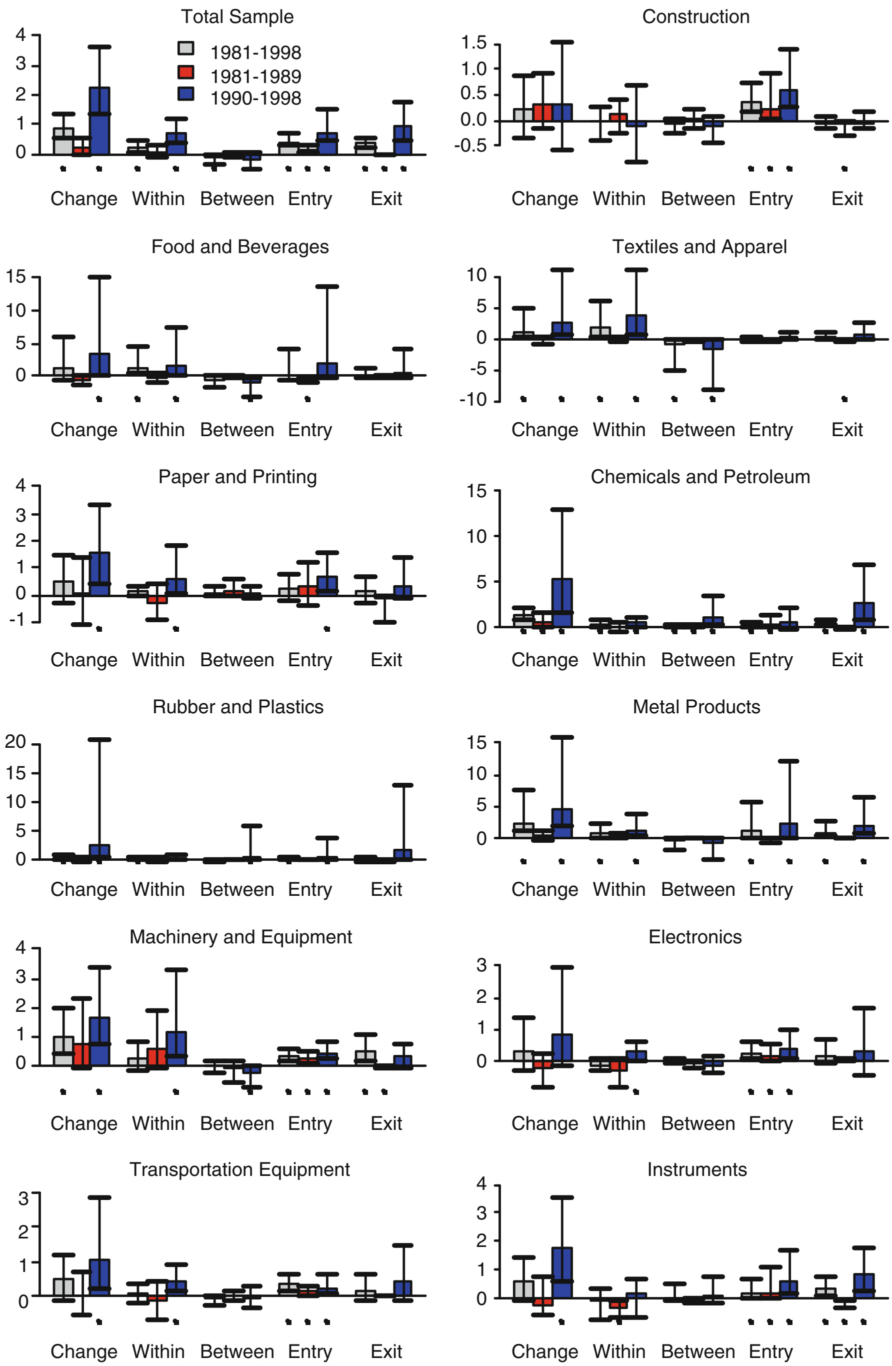

Fig. 13 GR decomposition for order-m productivity estimates with employment shares

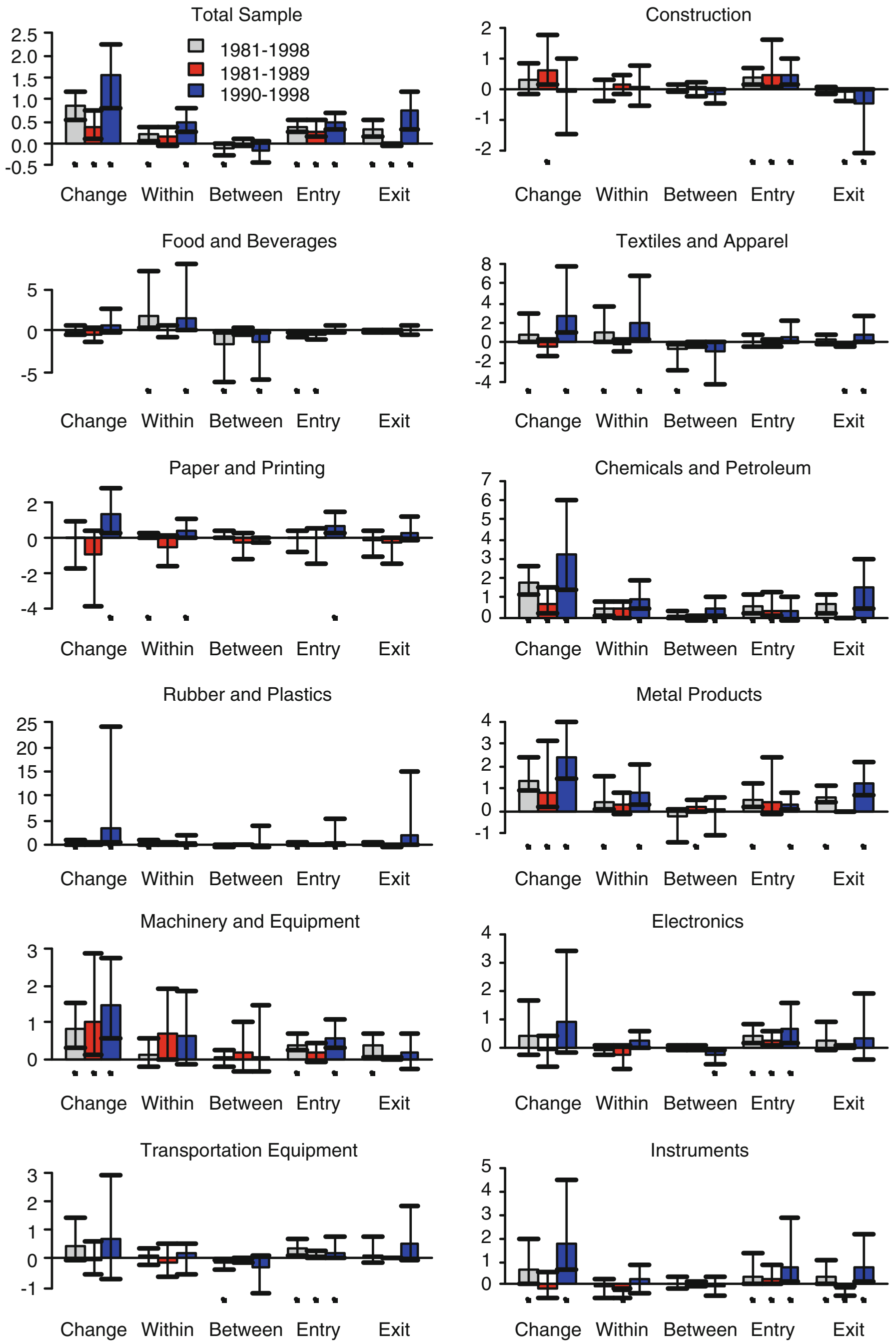

Fig. 14 GR decomposition for order-m productivity estimates with sales shares

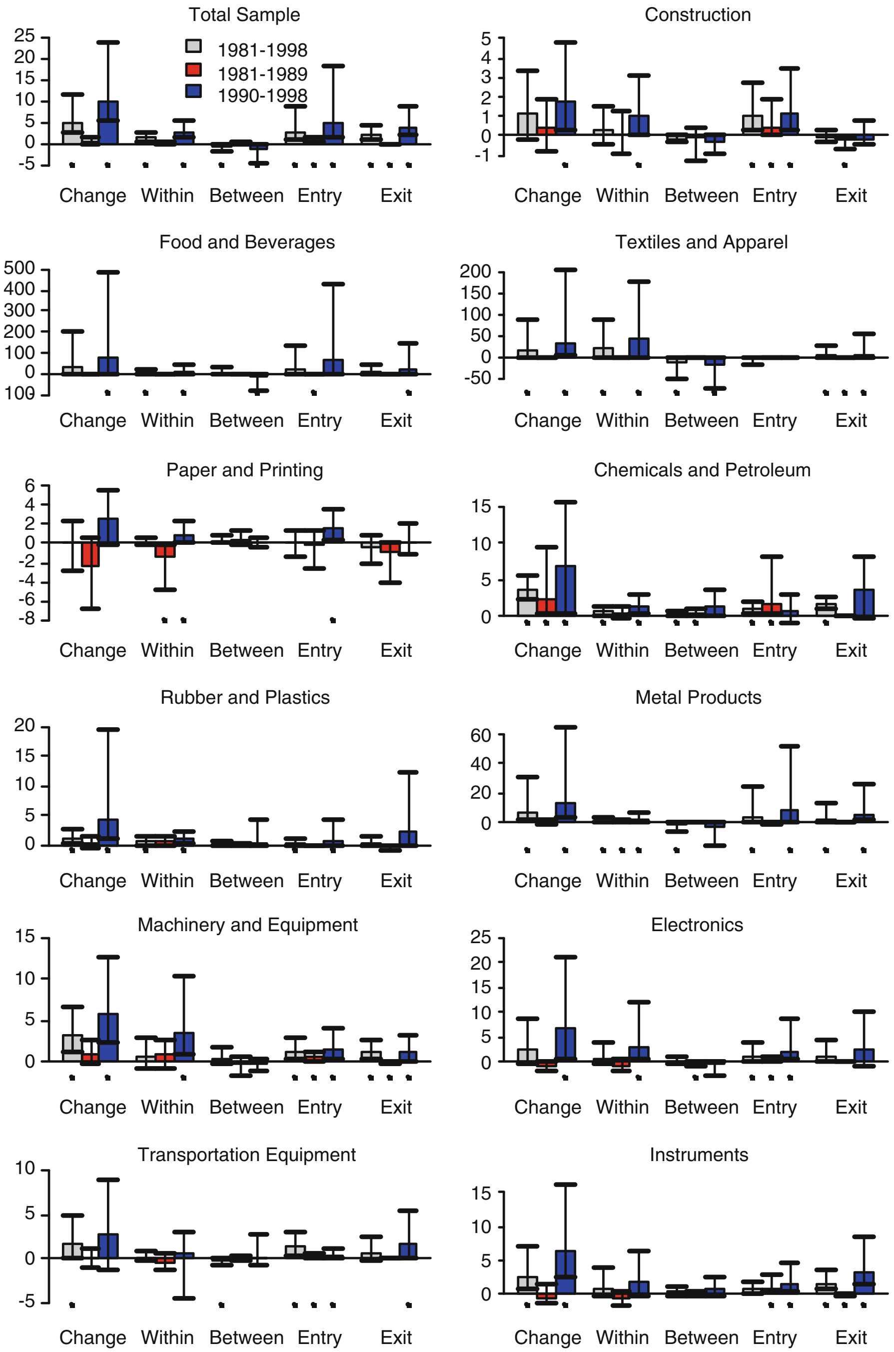

Fig. 15 GR decomposition for order-α productivity estimates with employment shares

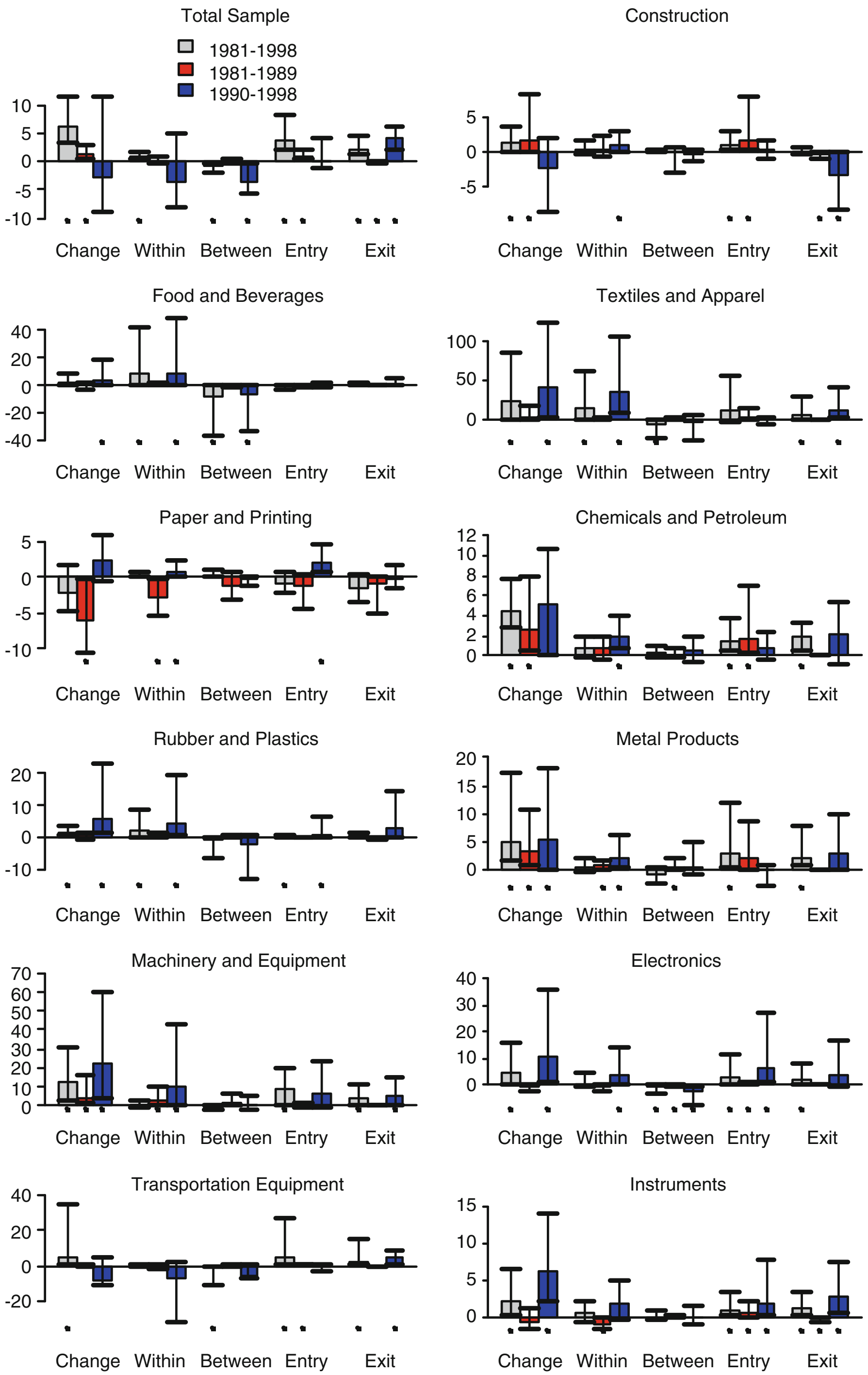

Fig. 16 GR decomposition for order-α productivity estimates with sales shares

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