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Intra-sectoral structural change and aggregate productivity development: a robust stochastic nonparametric frontier function approach

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A Robust Stochastic Nonparametric Frontier Function Approach

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A Robust Stochastic Nonparametric Frontier Function Approach

by

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Mai 2008

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Abstract:

This paper investigates the sources of total factor productivity growth in the German manufacturing sector, 1981-1998. Decomposition formulae for aggregate productivity growth are used to identify the effects of structural change and entry-exit on aggregate productivity growth. Documented is a substantial rise of 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 is the application of a robust stochastic nonparametric approach to frontier function analysis and the second is the calculation of bootstrap confidence intervals for the components of the productivity decompositions.

JEL classification: D24, O12, L60

Keywords: productivity decomposition, structural change, manufacturing

^{*} I thank Uwe Cantner for generously providing the data. Of course, he is not responsible for all what followed.

1. Introduction

Structural change within industries or sectors of an economy occurs because firms grow at different rates in terms of sales or employment. The 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, meaning 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. Thus, the differences in competitiveness should also be reflected in different levels of firm productivity and Balk (2003) shows that 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 of product market competition and total factor productivity growth.

Dynamic models in industry dynamics such as presented by Ericson and Pakes (1995), Lambson (1991), Luttmer (2007), Nelson and Winter (1982) or Winter et al. (2000, 2003), among many others, establish differential growth of firms as fuelled by the differential success of their innovative activities which are also associated with differential changes of productivity. By that, the models bear direct relations to Schumpeters (1942) notion of creative destruction and to the formal mechanism of replicator dynamics (see Metcalfe 1994) which can be conceived as a reduced-form representation of the elaborate models. 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.

The present paper focuses on the investigation of the association of productivity change and differential growth in terms of either employment or sales by means of productivity decomposition formulae. It is related to the study of Cantner and Krüger (2008) with two major technical improvements. The first improvement consists of the application of the recently developed order- m approach for robust stochastic nonparametric efficiency analysis. The second improvement is that the productivity decomposition formulae are not only used as a purely descriptive device to uncover the sources of aggregate sectoral productivity change (i.e. the contribution of structural change among the firms that are continuously in the sector and the role

entry and exit) but here estimation precision is also evaluated by computing bootstrap confidence intervals. Both improvements lead to an increased reliability of the findings and to a clearer judgement of which effects are really important and which are associated with substantial estimation error.

The plan of the paper is to start by giving a short outline of the order- m approach in the next section 2. This is followed by a description the two decomposition formulae applied and the discussion of the corresponding results in sections 3 and 4. Section 5 summarizes and concludes.

2. Order- m Productivity Measurement and Data

In contrast to traditional data envelopment analysis used in Cantner and Krüger (2008), the order- m approach to robust stochastic nonparametric efficiency measurement is applied here. The foundations of this approach are developed in Cazals, Florens and Simar (2002), while the approach has been made accessible for practitioners by Daraio and Simar (2005, 2007a,b).¹ As we will see shortly, the order- m approach combines the advantages of data envelopment analysis (DEA) and stochastic frontier analysis (SFA). It is both nonparametric (as DEA) and stochastic (as SFA). Being stochastic makes the approach robust since the frontier function is not forced to envelop all observations (including the outlying ones). In addition, the order- m approach has very favorable statistical properties for a nonparametric method.

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} denote 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). $H_{xy}(\mathbf{x}, \mathbf{y})$ can be decomposed as

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

¹ Especially the monograph of Daraio and Simar (2007b) is worth mentioning in this respect.

and this is the conceptual basis for defining the input-oriented 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 $S_Y(\mathbf{y}) > 0$. As a radial efficiency measure, $\theta(\mathbf{x}, \mathbf{y})$ gives the largest possible proportional reduction of all inputs so that the resulting input-output combination remains possible to realize (has a probability larger than zero). This defines the attainable set of inputs for a given output level. For a set of real data this efficiency measure could be computed by estimating $F_{X|Y}(\mathbf{x} | \mathbf{y})$ with the corresponding empirical distribution function.

The order- m approach takes as benchmark “the average of the minimal value of inputs for m units randomly drawn according to $F_{X|Y}(\cdot | \mathbf{y})$ ” (Daraio and Simar 2007a, p. 16). This amounts to taking a pre-specified 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 construct the *partial* technology set $\Psi_m(\mathbf{y}) = \{(\mathbf{x}, \mathbf{y}') \in R_+^{p+q} : \mathbf{x}_j \leq \mathbf{x}, \mathbf{y}' \geq \mathbf{y}, j = 1, \dots, m\}$. This is called a partial technology set because it is not constructed from the whole sample but only from the subsample of the m reference DMUs. The partial technology set is then used to define the input-oriented radial efficiency measure by $\tilde{\theta}_m(\mathbf{x}, \mathbf{y}) = \inf\{\theta : (\theta\mathbf{x}, \mathbf{y}) \in \Psi_m(\mathbf{y})\}$. From that, 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 computation of the order- m efficiency measure can conveniently be implemented as a Monte Carlo algorithm. For a sample of n DMUs with input-output combinations $(\mathbf{x}_i, \mathbf{y}_i)$, $i = 1, \dots, n$ 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 $(\mathbf{x}_j, \mathbf{y}_j)$, $j = 1, \dots, m$ 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 $\hat{\theta}_m^1, \dots, \hat{\theta}_m^B$ from which the order- m efficiency measure of DMU i is finally computed as the average $\hat{\theta}_m = B^{-1} \cdot \sum_{b=1}^B \hat{\theta}_m^b$.

As explained in Daraio and Simar (2007a), the single efficiency measure $\hat{\theta}_m^b$ against the partial technology frontier can be computed by a variety of nonparametric techniques, most notably data envelopment analysis (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 2007b), although a larger number of Monte-Carlo replications is preferred in the application of this paper. The results are usually very robust with respect to different choices for m , thus setting $B = 1000$.

The statistical properties of the order- m efficiency measure are very appealing. 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 whole sample has to be enveloped by the frontier function. This fact gives the procedure a great deal of robustness, while preserving the nonparametric nature of the efficiency measure. As Cazals, Florens and Simar (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 (the dimension $p + q$) of the problem – the so-called “curse of dimensionality”. Thus, the order- m approach gives us the best of all worlds with the advantages of both the nonparametric efficiency measurement methods like DEA and the statistical properties of stochastic frontier analysis. Order- m efficiency measures are nonparametric in that they neither require the specification of a functional form of the production function nor the specification of the distribution of the inefficiency term. Simultaneously, they are stochastic with the virtues of robustness and fast convergence to the asymptotic magnitudes.

In the following the order- m approach is implemented in the form of an all-time-best frontier estimation based on observations of a sample of 874 German manufacturing firms that operate at any time between 1981 and 1998. These firms are assigned to 11 industries at a roughly two-digit (SIC) level of aggregation. The 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 finally instruments.

Productivity is estimated as total factor productivity for each industry separately. Total sales from the profit and loss accounts, corrected for inventory changes and internally used firm services is used as the single output variable. Labor input is measured by the number of em-

ployees, 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 in the profit and loss accounts. All monetary variables are converted to real magnitudes using industry-specific price deflators from the 60-Industry Database of the Groningen Growth & Development Centre (O'Mahony and van Ark 2003). The data set is identical to that used in Cantner and Krüger (2008) where a full discussion of the data sources, the data handling and descriptive statistics can be found. The order- m estimates are computed using the package "FEAR" for R , supplied by Paul Wilson on his web page (see Wilson (2007)).

3. Decomposition of Foster, Haltiwanger and Krizan (FHK)

The direct approach for the assessment of the contribution of structural change to aggregate productivity growth taken here is to construct a measure of aggregate productivity growth and to decompose this measure into several additive terms, each with an own economic interpretation. Let a_{it} denote the productivity level of firm i in period t and s_{it} the corresponding share in total employment or sales. Then the measure of aggregate productivity growth based on the change of share-weighted aggregate productivity can be expressed as

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

where $\bar{a}_t^s = \sum_{i \in C \cup N} s_{it} a_{it}$ and $\bar{a}_{t-k}^s = \sum_{i \in C \cup X} s_{it-k} a_{it-k}$ denote the share-weighted aggregate productivity levels of periods t and $t-k$ ($k > 0$), respectively. 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 $C \cup N \cup X = \{1, \dots, n\}$). Entry and exit is taken into account by the fact that $s_{it-k} = 0$ in the case of the entering and $s_{it} = 0$ in the case of the exiting firms. With this notation, the average percentage growth rate of share-weighted aggregate productivity over the period t to $t-k$ 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 in Foster, Haltiwanger and Krizan (1998), which is an extension of the formula of Baily

et al. (1992) that also accounts for the contributions of entering and exiting firms. Accordingly, $\Delta \bar{a}_t^s$ can be decomposed into

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

where Δa_{it} and Δs_{it} denote $a_{it} - a_{it-k}$ 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 change 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 (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 their shares (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 mean, the covariance component relates share changes to productivity changes. It is apparent that the between component exactly corresponds to the effect of the replicator dynamics mechanism explained in the introduction.

The final two terms of the formula contain the contributions of the entering and exiting firms to aggregate productivity growth. These represent the *entry* and *exit* components. The contribution of an entering firm to aggregate productivity growth is positive if it has a productivity level above the initial average, and the contribution of an exiting firm to aggregate productivity growth is positive if its productivity level 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 recognize that these are sums over heterogeneous samples of firms. Thus, the positive (or negative) sign of a component results from an overweight of the positive (or negative) contributions of a part of the sample firms over the contradicting contributions of the remaining part of the sample. In no case it is precluded that positive and negative contributions from individual firms cancel out to a considerable extent.

The shares required for the aggregation are specified either as the shares of the firms in total employment or as the shares of the firms in total sales. The results of the decomposition are shown in graphical form in the following figures with the total sample in the upper left panel and the eleven industries in the remaining positions. Each component of the decomposition is shown by 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.² Space considerations require collapsing the entry and exit components into a joint net entry component. The separate consideration of the entry and exit components will be picked up in the next section.

Reported together with each bar is a 95 percent confidence interval computed via bootstrapping shown by two horizontal bars connected with a vertical line. These confidence intervals are computed as bias-corrected and accelerated (BC_a) confidence intervals according to Efron (1987), and also explained in Efron and Tibshirani (1993, ch. 14). All bootstrap confidence intervals are computed using the *R*-package “boot” accompanying the book of Davison and Hinkley (1997) based on 10000 replications. A dot below a confidence interval indicates that the confidence interval does not cover the zero value and thus indicates statistical significance. As far as I know, this is the first time that the estimation uncertainty associated with the components of productivity decompositions is assessed at all.

A first set of results using employment shares for aggregation is shown in figure 1. Concentrating on the first plot for the total sample of firms we observe statistically significant aggregate productivity change for the whole sample period. This appears to be mainly driven by the development during the second subperiod after 1990. Relatedly, the literature reports widespread evidence of much larger productivity growth during the 1990s, compared to the period before 1990 for the majority of European countries in addition to the US and Canada. Especially the first half of the 1990s plays an important role for that outcome.³

² It is worth stressing at this point that the differences found in the subperiods before and after the German reunification can not easily 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.

³ See for example van Ark et al. (2008) for a deeper discussion of the reasons underlying these developments.

Figure 1
FHK-Decomposition with Employment Shares

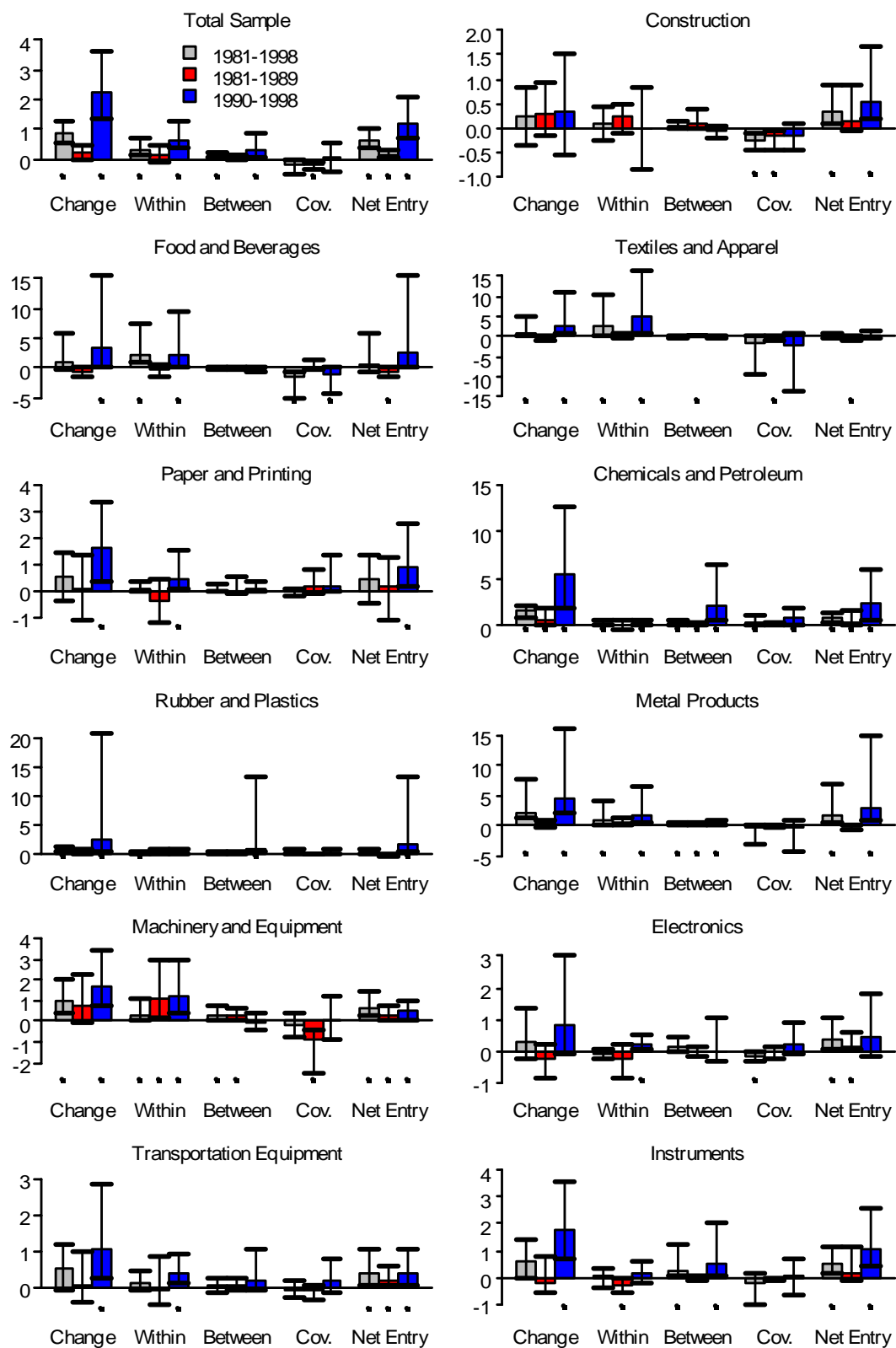
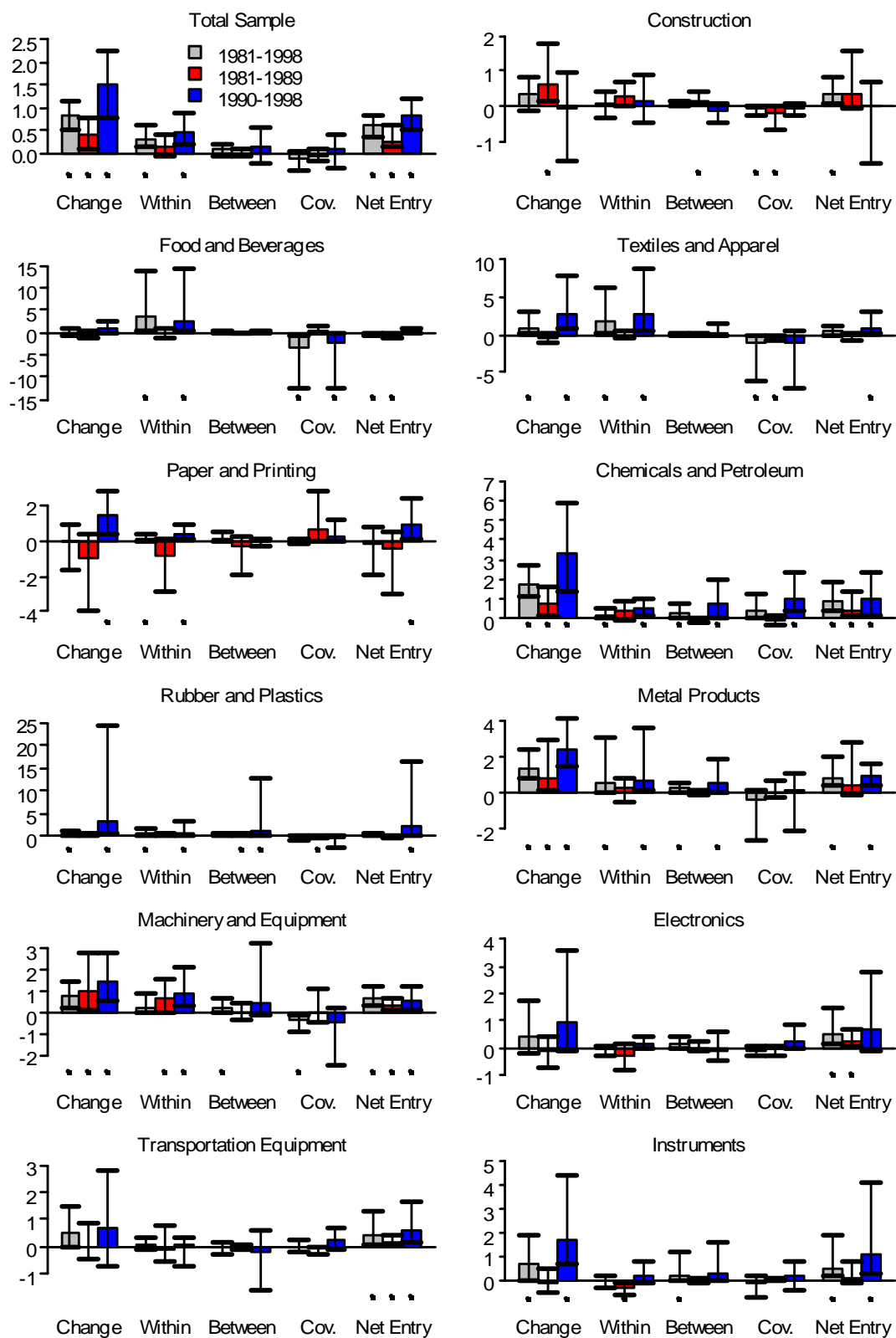


Figure 2
FHK-Decomposition with Sales Shares



For these differences in productivity growth the within component representing internal firm learning, of course plays a role and is also statistically significant during the whole 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 applies primarily to the between component which is positive and thus reflects the selection mechanism postulated by replicator dynamics (recall that according to replicator dynamics firms with above (below) average productivity levels tend to have increasing (decreasing) employment shares). The net entry component 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 much larger during the second subperiod compared to the first.

In sum, aggregate productivity change in the period after the German reunification is fuelled by the within component (about 30 percent), the between component (about 20 percent) and by the net entry component (about 50 percent), whereas the covariance components appears not so important. By that, the components related to structural change are able to explain the bulk of the aggregate productivity change during that period.

Looking at the other plots in the figure, pertaining to the eleven individual industries, the same basic pattern as for the total sample of firms can be observed. In some industries, however, the confidence intervals appear to be rather wide due to the reduced 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 confidence intervals in these cases, the significant effects have the right sign, here also supporting the overall conclusions for the total sample and the other individual industries. Structural change appears to be particularly important for chemicals and petroleum and instruments. For some industries the covariance component is negative (implying that productivity and share changes tend to go in different directions) and sometimes also significantly so. Aside of rare exceptions, the covariance component appears not to be very important quantitatively.

The corresponding results with sales shares instead of employment shares for computing the components of the decomposition formula are shown in figure 2. Although there are differences to the results with employment shares the basic pattern appears robust and the essential aspects of the interpretation go through modified. In the case of the total sample, the between

component is not significant in any period when sales shares are used for the aggregation. The contribution of the net entry component remains predominantly positive and is quite large in magnitude for the total sample and the majority of the industries.

4. Decomposition of Griliches and Regev (GR)

In this section, we turn to an alternative decomposition. This decomposition is due to Griliches and Regev (1995) and is deemed to be more robust with respect to outliers in the data. A disadvantage 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 results above. Foster et al. (2008) provide a modified version of the Griliches-Regev formula to decompose the numerator of the aggregate productivity growth rate as follows

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

using the above introduced notation and in addition $\bar{a}_i = \frac{1}{2}(a_{it} + a_{it-k})$, $\bar{s}_i = \frac{1}{2}(s_{it} + s_{it-k})$ 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. (1998) is that the effects are now based on the average productivities and shares (\bar{a}_i , \bar{s}_i and \bar{a}^s) which renders the estimation more robust and that the covariance effect is no longer present.

Analogous to the FHK decomposition, the results are reported in figure 3 for employment shares and in figure 4 for sales shares. The missing covariance component allows now to show the entry and exit components separately, thus completing the analysis of the previous section in this respect. Confidence intervals are again computed as BC_a bootstrap confidence intervals whenever possible. In two cases, rubber and plastics and transportation equipment during the first subperiod 1981-89, this proved not to be possible and bootstrap percentile intervals with the same number of replications are reported instead.

Figure 3
GR-Decomposition with Employment Shares

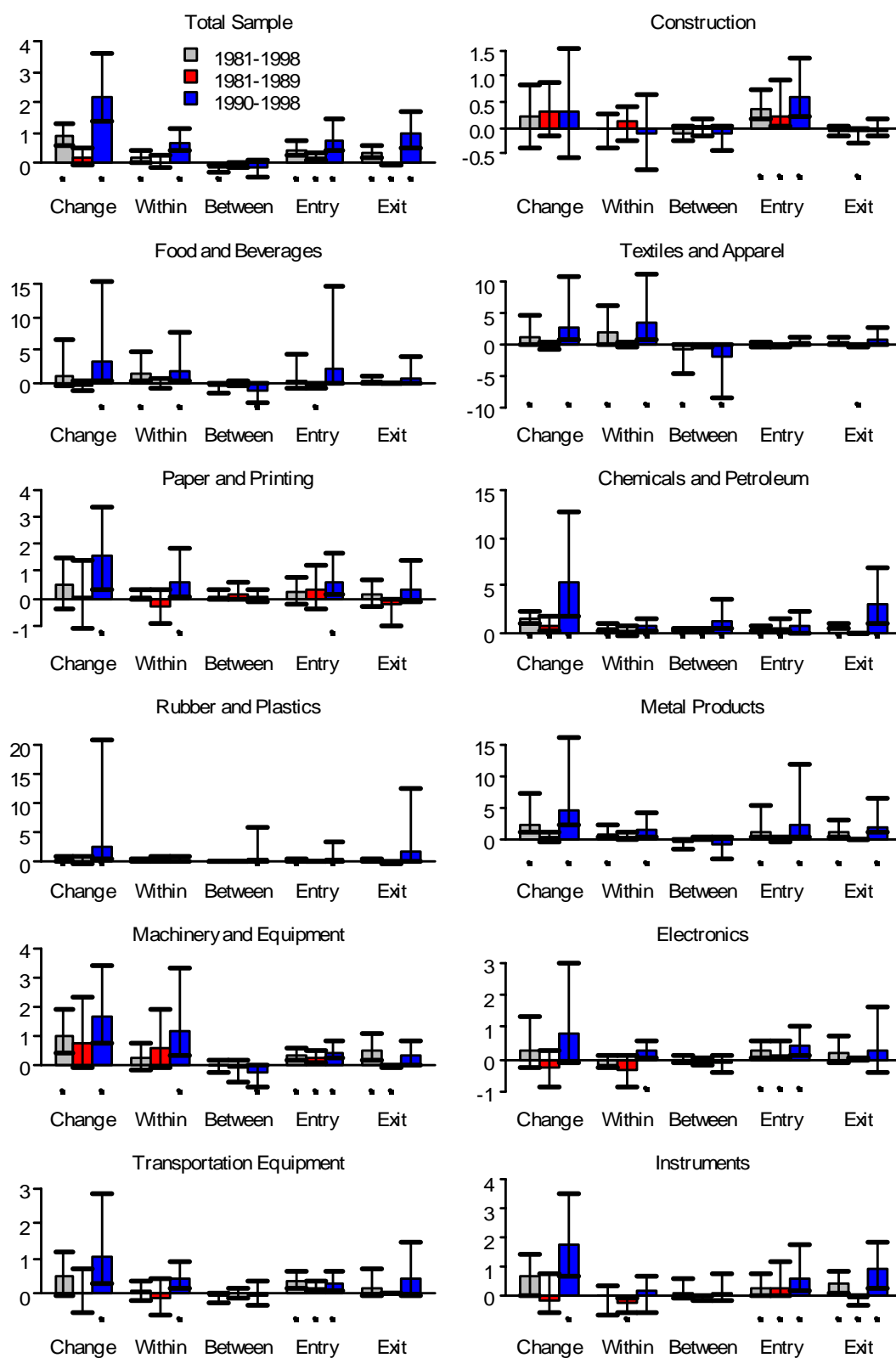
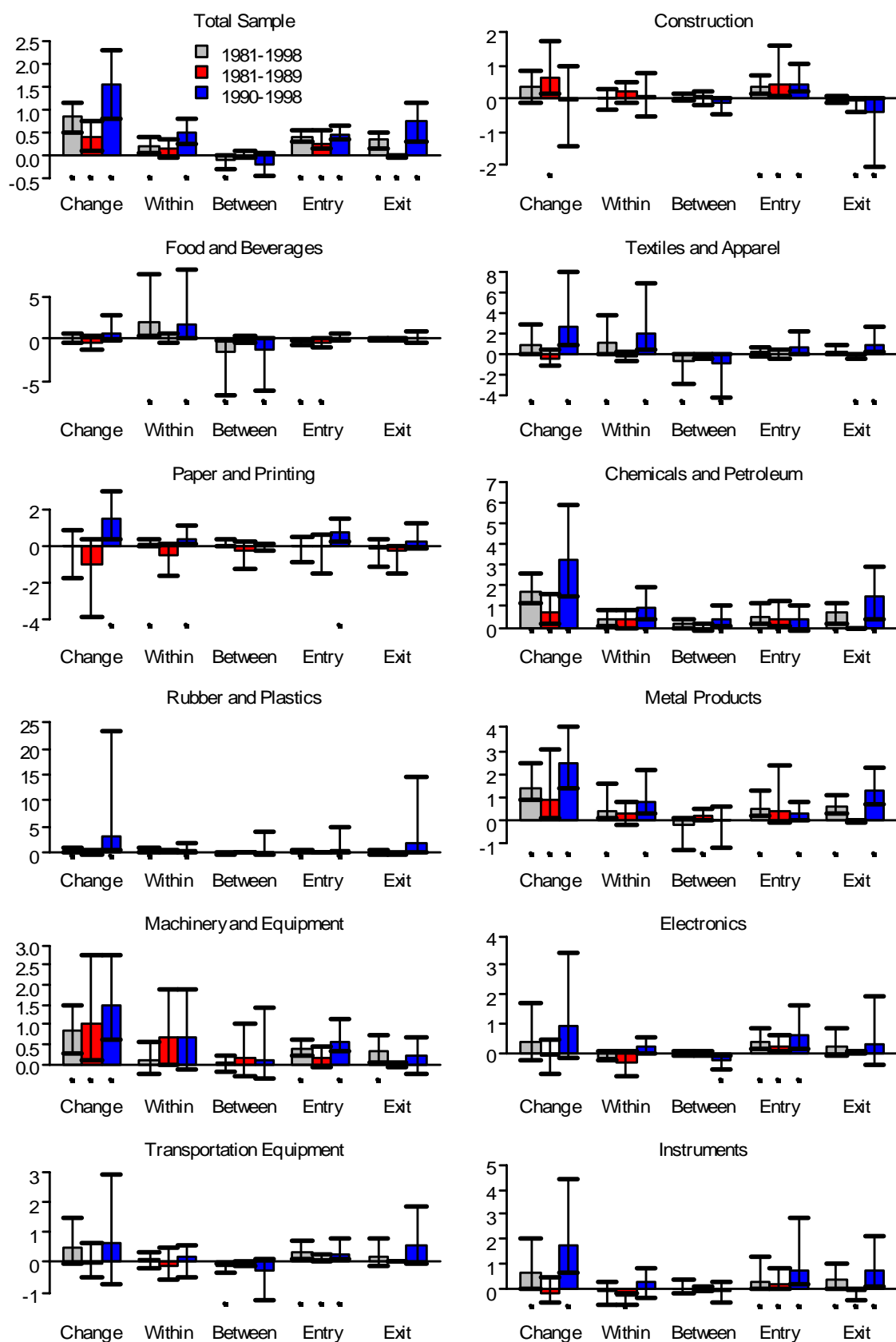


Figure 4
GR-Decomposition with Sales Shares



From the figures it can be inferred that the modified between component is negative and only significant in the first subperiod for the total sample, irrespective of the mode of shares. This should not prematurely be interpreted as evidence against selection according to the replicator mechanism since the between component is here modified compared to the previous decomposition. It is not the difference of the initial period ($t - k$) productivity level of firm i to the previous period (share-weighted) average productivity level which is related to the share change in the Griliches-Regev formula. Instead, the difference is based on the averages of the actual and previous 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 between component. This applies in particular to the case of food and beverages where the modified between component is significantly negative for the total period and the second subperiod, approximately offsetting the positive effect from the within component.

Concerning the contributions of entry and exit the results reveal that the large contribution of net entry is likewise caused by the entry and the exit component. An explanation for the entry effect may be that entering firms are endowed with machinery and equipment of more recent vintages that are naturally associated with higher levels of total factor productivity. This holds for the total sample as well as for the majority of the individual industries and time periods and is also robust to the utilization of employment or sales shares for the aggregation. Firms which are forced to exit especially in the second subperiod have productivity levels considerably below the average.

5. Conclusion

Considered together, the results reported in this paper, generated with the recently developed robust stochastic nonparametric order- m approach 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 the individual firms makes an important contribution, but the structural change among the continuing firms can also explain a considerable part. Third, of major importance is the contribution of entry and exit, where especially entering firms predominantly have above-average productiv-

ity levels. Fourth, this pattern largely holds when all firms are pooled together irrespective of their industry assignment as well as for most of the individual industries considered.

The results match findings of Baldwin and Gu (2006) for Canada, Disney et al. (2003) for the UK and Foster et al. (1998) for the US.⁴ Note that these studies operate on the level of establishments whereas the present study is on the level of firms. With the methodological refinements implemented here, the essential results of Cantner and Krüger (2008) could also be confirmed, although some effects appear to be attenuated with the robust approach. This holds true in particular for the covariance component. In addition to the application of the robust order- m approach the second methodological contribution of the present paper is the computation of confidence intervals for the components of the productivity decompositions. Overall, the confidence intervals revealed that the results from productivity decompositions frequently are associated with substantial estimation uncertainty.

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 containing the association of the changes of shares and productivity levels. This shows again that the relation of technological performance (in a broad sense measured by productivity change) to the economic success or failure of firms is of a very complicated nature and should remain high on the agenda for further research.

⁴ See also the survey articles by Bartelsman and Doms (2000) and Haltiwanger (2000). Krüger (2008) contains a review of the literature mostly concerned with the level of sectors.

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