Technological and Economic Mobility in Large German Manufacturing Firms

by

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Abstract:

Using data for large quoted German manufacturing firms that pertain to different industries we calculate output shares as well as non-parametric measures of total factor productivity. Based on these we visualize the amount of mobility by the construct of Salter curves and quantify mobility by mobility indices. The mobility of the total factor productivity measures is related to technological competition whereas the mobility of the output shares relates more closely to economic competition. We interpret technological mobility as an indicator for the differential success of the implementation of technological innovations and economic mobility as an indicator for the resulting differential economic success. Our results show substantial differences in the mobility of total factor productivity between industries but rather low mobility differences in the case of output shares. Comparing the mobility of total factor productivity to the mobility of output shares we find a much higher persistence (which is equivalent to lower mobility) in the case of the latter.

JEL classification: L11, O30, C10, C23

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1. Introduction

The analyses reported in this paper refer to the relationship between firm performance on the one hand and firm and industry evolution on the other. The empirical literature on this so-called industrial dynamics starts its analyses from a number of stylized facts related to structure and structural change (see Dosi et al. 1997). Among those structural factors of considerable importance is the heterogeneity or asymmetry of firms which suggests a strongly idiosyncratic element in the technological performance of firms on the one hand and their economic performance on the other hand. The dynamics and evolution of an industry is then consequently to be seen as determined by the development of these different heterogeneities over time.

There is some confusion in the recent literature on industrial dynamics about the amount of persistence or variability of certain variables like market shares or productivity measures over time. On the one hand, empirical studies like those of Geroski and Toker (1996) for market shares or Jensen and McGuckin (1997) for relative labor productivity found considerable persistence of those measures. On the other hand, studies of Davies and Geroski (1997) or Mazzucato and Semmler (1999) came to the result that market shares are rather unstable. Geroski (1998) surveys the literature of large company performance and added new results for a balanced panel of 280 large quoted UK companies over the period 1972-82. From all this evidence he then synthesized the results into a number of stylized facts, two of which are of special interest for the investigation in the present paper. These are stylized fact #3 which states that heterogeneities in economic performance between firms persist into the long run more or less regardless of how performance is measured and stylized fact #5 which claims that most firms are irregular and erratic innovators when innovations are measured by counts of major innovations.

Much of the empirical work in this field either uses regression estimates to find out the determining factors of structural change or focuses completely on descriptive measures of the evolution of the shape of the distribution. In this paper we take a different line of research in that we abstract from the shape of the distribution and the determinants of changes herein. Instead we want to investigate the dynamics that are present under the distribution (intra-distribution dynamics) and therefore employ two methods that are capable to visualize or quantify the amount such intra-distribution mobility. The first method relies on the concept of

Salter curves developed by Salter (1960). These represent the ranking of observations (characterizing the structure) and allow to judge the extent of mobility within this ranking by comparing the Salter curves pertaining to different periods. The second method supplements the graphical Salter curve approach by quantifying the extent of mobility through the calculation of mobility indices which map the information of a Markov transition matrix into a scalar measure (Geweke et al. 1986, Shorrocks 1978).

The plan of the paper is as follows. In section 2 the data and the methodology used to measure total factor productivity are described. Section 3 contains the results on mobility obtained by Salter curves. As a quantitative measure of mobility section 4 introduces mobility indices based on Markov chains and presents the results we achieved with this method. Section 5 concludes with some interpretations.

2. Data and Productivity Measurement

The data used in our analysis refer to a sample of large German manufacturing firms observed over the period 1981-93. The manufacturing sector is divided in eleven industries which are chemistry, electronics, precision mechanics/optics, plastics and rubber, machinery, automobiles, iron and steel, paper and board, construction, beverages and textiles. With respect to the firms only quoted companies are included in the sample. The data we use are all drawn from the balance sheets and the annual reports of the respective firms. For the determination of the productivity scores we use a model with a single output variable and the inputs inputs labor, capital and material are used. Labor is measured in effective hours worked, capital is computed by the perpetual inventory method using data of investment and disinvestment and a technical rate of depreciation, materials is the deflated gains-and-loss position "raw materials and supply". For the output the deflated sum of "total sales", "inventory changes" and "internally used firm services" from the profit and loss accounts is computed. The same output variable is used to compute the firms' respective (real) output shares.

As to the determination of the technological performance we apply a measure of total factor productivity. For its determination we refer to a procedure discussed in much more detail in Cantner and Hanusch (2001). Applications of this approach are found in a number of other papers (see e.g. Bernard, Cantner and Westermann (1996), Cantner, Hanusch and Westermann (1996), Cantner and Westermann (1998) and Krüger, Cantner and Hanusch (2000)). Since a more detailed discussion of the procedure is contained in the above cited paper we provide only a brief sketch in the following.

The approach attempts to determine the heterogeneous technological performances of firms belonging to the same industry. By applying a non-parametric linear programming method a so-called best-practice technology frontier function is determined. For this purpose data for the real input factors and the real outputs are used. The non-parametric specification allows to treat each firm as producing with a Leontief production function which may be quite different from the production functions of the other firms. The respective linear program for a specific firm l can be compactly stated in matrix form:

$$
\begin{array}{lcccccccc}
\min & \theta_l & - & \varepsilon \mathbf{e}^T \mathbf{s}^+ & - & \varepsilon \mathbf{e}^T \mathbf{s}^- & & \\
\text{s.t.} & & & & & & & \\
 & & & \mathbf{Y\lambda} & - & \mathbf{s}^- & = & \mathbf{y}_l \\
 & \theta_l \mathbf{x}_l & - & \mathbf{X\lambda} & - & \mathbf{s}^+ & = & \mathbf{0} \\
 & & & & & & & \\
\mathbf{\lambda}, \mathbf{s}^+, \mathbf{s}^- & \geq & \mathbf{0} & & & & &
\end{array}
$$

θ_l is the scalar productivity score of firm l with $\theta_l \in (0,1]$. A productivity score $\theta_l = 1$ is obtained if firm l is best-practice and $\theta_l < 1$ indicates that the firm is below best-practice. $\mathbf{s}^+$ and $\mathbf{s}^-$ are excess inputs and output-slacks respectively, $\mathbf{e}^T$ is a vector containing only ones and ε is a so-called non-archimedian constant which is necessary to identify cases where firms are determined as best-practice although they obviously are not.[1] $\mathbf{Y}$ and $\mathbf{X}$ denote the matrices of all n firms outputs and inputs, respectively. $\mathbf{y}_l$ and $\mathbf{x}_l$ are the vectors of firm l's outputs and inputs. $\mathbf{\lambda}$ is a vector which contains the respective weights of the firms among the n that serve as the reference points against which the productivity of firm l is determined.

For measuring the economic performance of firms we refer to an output measure, the so-called output share which is the share of output of firm l in the total output of the firms in the respective industry in a specific year. In order to make this measure comparable in construction to the measure of relative productivity we normalize it by dividing the output

[1] On this issue see Cantner/Hanusch/Westermann (1996).

share of firm l by the largest output share in firm l′s industry in the same period. Consequently, like the productivity scores the normalized output shares are bounded in the interval (0,1] where one is the largest normalized share.

Table 1 states for each industry some descriptive statistics with respect to the productivity scores and the normalized output shares. The last column gives information about the number of firms in each industry.

Table 1
Descriptive Statistics

	Productivity Scores		Normalized Output Shares		
Industry	*Mean*	*CoeffVar*	*Mean*	*CoeffVar*	*#Firms*
Chemistry	0.79	0.18	0.12	1.86	52
Electronics	0.77	0.18	0.07	2.46	36
Precision Mechanics/Optics	0.95	0.07	0.26	1.31	11
Plastics and Rubber	0.88	0.13	0.21	1.28	21
Machinery	0.82	0.15	0.15	1.42	83
Automobiles	0.95	0.06	0.19	1.46	15
Iron and Steel	0.85	0.12	0.17	1.44	37
Paper and Board	0.90	0.11	0.39	0.82	13
Construction	0.93	0.07	0.22	1.30	22
Beverages	0.78	0.17	0.16	1.23	62
Textiles	0.81	0.16	0.26	1.03	40

From table 1 we obtain the eye-catching result that the coefficient of variation (abbreviated by CoeffVar in the table and calculated as the standard deviation divided by the arithmetic mean) is substantially higher for the output shares of the different industries as compared with the productivity scores. This means that the distribution of the output shares is more dispersed than the distribution of the productivity scores and may be interpreted in terms of higher fluctuations. But since the coefficient of variation (as a measure of dispersion) is more a measure of the shape of the distribution rather than a measure of intra-distributional change a more dispersed distribution may be the result of larger heterogeneity of the sample which is totally consistent with a scenario of unaltered positions of the observations relative to each other. To abstract from the shape of the distribution and to focus on the amount of intra-distributional change we subsequently employ two different methods that are capable to visualize or quantify the amount of intra-distributional change which we will simply call mobility.

3. Salter Curves

In order to visualize the amount of mobility in the productivity scores and the output shares we use the concept of Salter curves, named after their first use in a productivity context by Salter (1960). A Salter curve depicts the variable under examination after sorting the observations of this variable in a descending order. A visual impression of the heterogeneity in the sample can then easily be obtained from the slope of the Salter curve. A larger (negative) slope represents a more heterogeneous sample whereas complete homogeneity would result in a horizontal Salter curve. Salter curves of subsequent periods are plotted with the firms sorted in the same order as the firms of the first period so that regions of decreasing or increasing heterogeneity can be identified by looking where the Salter curve of a later period lies above or below the Salter curve of the first period.

In the following figures 1 and 2 the first period Salter curve is given by the solid line, where we take the mean of the productivity scores (respectively output shares) over the period 1981-85 as the variable under examination. The Salter curves for the means of the subsequent periods 1985-89 and 1989-93 are drawn by the dashed and dotted lines, respectively. In both cases it is important to keep in mind that the observations are still sorted in the order of the first period (1981-85). Now we can easily see where heterogeneity gets larger and where it gets smaller compared to the first period. In regions of the plot where a Salter curve is below the Salter curve of the preceding period firm heterogeneity has been increasing and in regions where the Salter curve of the subsequent period lies above the Salter curve of the preceding period heterogeneity has been decreasing. The magnitude of the deviations of subsequent period Salter curves can therefore be used as a visualization of the amount of mobility in the sample with respect to the variable under consideration.

Figure 1 presents the Salter curves for the productivity scores. They show us the development of the heterogeneity of the firms with respect to their technological performance. For the industries chemistry, electronics, paper and board, beverages and textiles we find that the technological heterogeneity of the firms has increased since the more recent Salter curves are (by and large) below the former ones. A contrariwise development is found for precision mechanics/optics, plastics and rubber, machinery, automobiles, iron and steel, and construction. In these cases the Salter curves of the more recent periods are mainly above the Salter curves of the later periods.

Figure 2 depicts the respective Salter curves for the output shares. First of all we recognize that the changes in the Salter curves here are of a much lower magnitude compared to the ones observed for the productivity scores. Thus, in general we find that the Salter curves in figure 2 are much closer to each other than in figure 1 which points to a more stable development of the normalized output shares than of the productivity scores. Concerning the development of heterogeneity in normalized output shares we see that for electronics, plastics and rubber, machinery, textiles and to a lower degree for chemistry as well as iron and steel there is a tendency for an increase. Contrariwise for precision mechanics/optics, automobiles, paper and board, construction and beverages the heterogeneity in the output shares has decreased.

The overall impression obtained from the figures 1 and 2 is that in our sample of large German manufacturing firms economic mobility (measured by the output shares) is substantially smaller than technological mobility (measured by the productivity scores). This result corresponds perfectly to the two stylized facts established by Geroski (1998) we mentioned in the introduction. Using a completely different set of empirical methods based on descriptive statistics, correlation coefficients, analysis of variance and panel autoregressions with fixed effects Geroski also found that technological mobility is larger than economic mobility.

Figure 1
Salter Curves for Productivity Scores

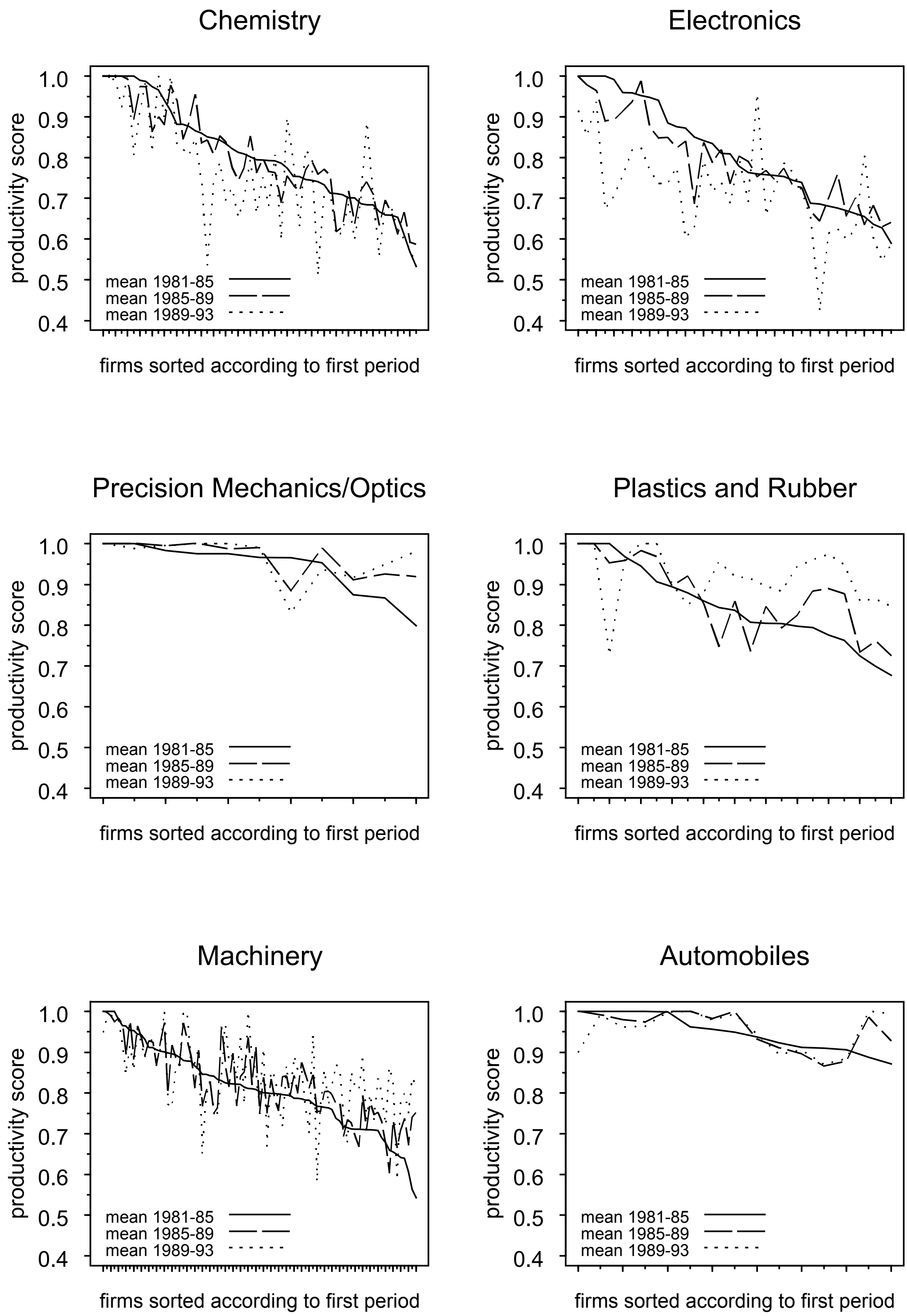


Figure 1
Salter Curves for Productivity Scores (continued)

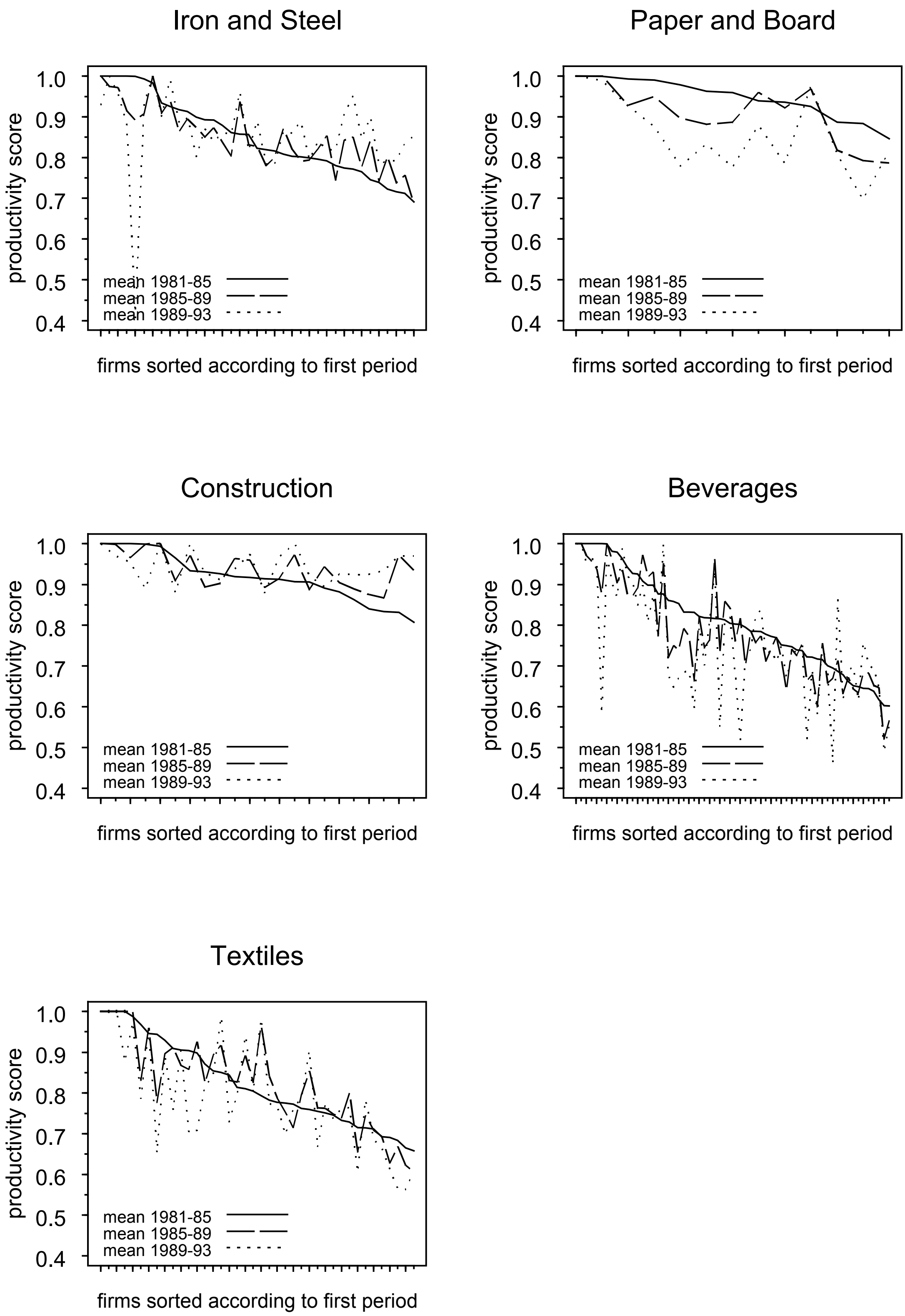


Figure 2
Salter Curves for Normalized Output Shares

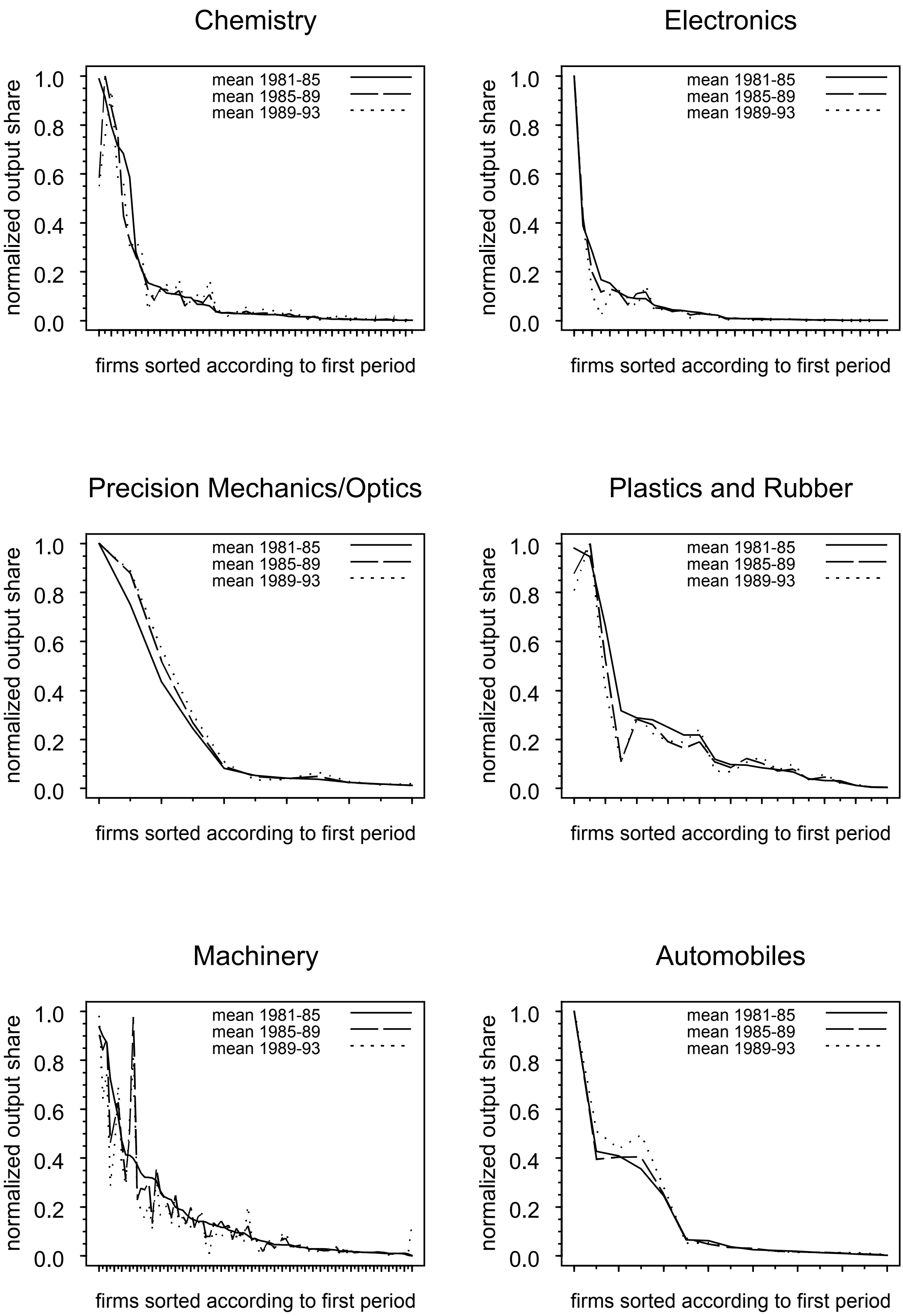
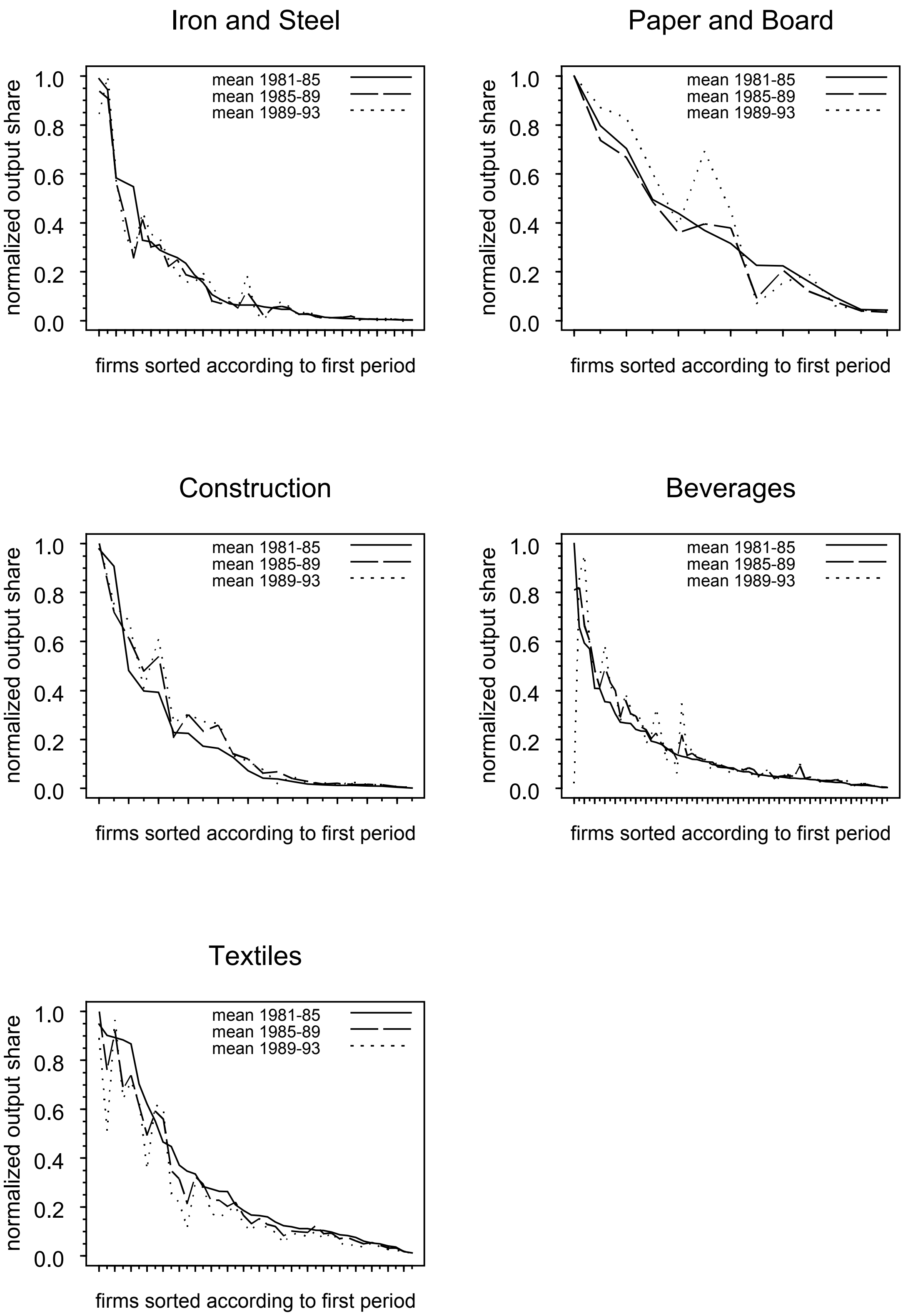


Figure 2
Salter Curves for Normalized Output Shares (continued)



4. Mobility Indices

Salter curves are a very useful instrument to visualize the amount of mobility in a panel, but since they rely on the discriminatory power of the viewer a comparison of the results with a more objective quantitative measure of mobility would be valuable. One class of such measures are mobility indices based on the estimated transition matrix of a Markov chain.[2]

The basis for the definition of a mobility index is the transition matrix of a Markov chain (see Norris (1998) for a book-length overview of Markov chains). The homogeneous first-order Markov chain we use in this paper is a stochastic process in discrete time $\{x_t\}_{t=1,2,...}$ which can assume n different states $x_t \in I = \{1,...,n\}$ and the movements between the states are controlled by a $n \times n$ transition matrix $\mathbf{P}$ with elements defined by

$$p_{ij} = \Pr(x_t = j \mid x_{t-1} = i);\ i,j \in I \text{ where } \Sigma_{j\in I}\, p_{ij} = 1\ \forall i \in I .$$

To understand how a mobility index works it is essential to remember that large elements on the main diagonal of the transition matrix indicate a high propensity to stay in a certain state in the next period, whereas large off-diagonal elements indicate a high propensity to move from one state to another between two periods. The aim of mobility indices (see Geweke et al. 1986 and Shorrocks 1978) is to weight the magnitude of the off-diagonal elements of a transistion matrix against the magnitude of the diagonal elements in a consistent manner. Precisely, mobility indices are continuous real scalar valued functions $M(\cdot) \in [0,1]$ over the set of transition matrices that provide a ranking of transition matrices with respect to mobility in that $\mathbf{P}_1$ is said to be more mobile than $\mathbf{P}_2$ if $M(\mathbf{P}_1) > M(\mathbf{P}_2)$.

One natural requirement which is imposed on mobility indices is that the identity matrix will be ranked lower than any other transition matrix, $M(\mathbf{I}) = 0$, since it represents a Markov chain that is characterized by complete immobility (the probability to stay in a certain state is exactly equal to one for all states). Additional criteria that a mobility index should fulfill are stated in Shorrocks (1978, pp. 1014f.). Before we describe the particular examples of mobility indices we use in this paper it should be noted that "no single mobility statistic has the minimum requirements regarded as essential" (Shorrocks 1978, p. 1023). Following this advice we consider various mobility indices simultaneously in order to obtain a valid summary picture of what is going on in the data with respect to the specific aims of our analysis.

The particular mobility indices we use in this paper are stated in the notation of Geweke et al. (1986, pp. 1409f.):

$$M_B(\mathbf{P}) = \Sigma_{i\in I}\pi_i \Sigma_{j\in I}\, p_{ij}\,|\, i-j\,|$$

$$M_U(\mathbf{P}) = n\Sigma_{i\in I}\pi_i(1-p_{ii})/(n-1)$$

$$M_P(\mathbf{P}) = (n - \mathrm{trace}(\mathbf{P}))/(n-1)$$

$$M_E(\mathbf{P}) = \left(n - \Sigma_{i\in I}\,|\,\lambda_i(\mathbf{P})\,|\right)/(n-1)$$

$$M_2(\mathbf{P}) = 1 - |\,\lambda_2(\mathbf{P})\,|$$

$$M_D(\mathbf{P}) = 1 - |\,\det(\mathbf{P})\,|$$

$M_B(\cdot)$ is called Bartholomew's index and has the feature of giving larger changes a higher weight than smaller changes. For its calculation the vector of stationary probabilites $\boldsymbol{\pi} = (\pi_1,\dots,\pi_n)'$ with $\boldsymbol{\pi} = \mathbf{P}\boldsymbol{\pi}$ is needed. Also based on stationary probabilites is the index $M_U(\cdot)$ which is simply defined as the unconditional probability of leaving the current state, scaled by $n/(n-1)$. $M_P(\cdot)$ is the trace index introduced by Shorrocks (1978, p. 1017). It is the inverse of the harmonic mean of expected durations of remaining in each state, scaled by $n/(n-1)$. The eigenvalue index $M_E(\cdot)$, where $\lambda_i(\mathbf{P})$ is the *i*-th largest eigenvalue of **P**, is positively related to the average rate of convergence of the chain towards its ergodic limit. It is identical to the trace index in the case of all eigenvalues real and positive since the trace of a matrix is the sum of its eigenvalues. Since Markov transition matrices always have one eigenvalue equal to unity and all other eigenvalues not larger than one in modulus, the second largest eigenvalue dominates the asymptotic rate of convergence of the chain and this fact is captured by the second eigenvalue index $M_2(\cdot)$. Finally the determinant index $M_D(\cdot)$ is

[2] Applications of mobility indices in economics include among others Mancusi (2000) for quantifying mobility in technological specialization, Proudman and Redding (1998) and Redding (2001) for measuring mobility in international trade specialization and Quah (1996) for analyzing regional output fluctuations in the US states.

related to the average magnitude of the moduli of the eigenvalues originating from the equality of the determinant and the product of all eigenvalues.

The following tables 2 and 3 comprise the results of the mobility index calculations for output share and productivity measures, respectively. All mobility indices are based on transition matrices estimated consistently by the maximum likelihood which calculates each transition probability estimate p_{ij} by the number of transitions from state *i* to state *j* divided by the number of times the chain leaves state *i* (Norris 1998, p. 56). The results are given for a four-state Markov chain where the states are determined so that the observations of the initial period are equally distributed across the states.

In table 2 we see that the rankings of the industries according to the different mobility indices with respect to the productivity scores are quite consistent with each other. Industries that show consistently low productivity mobility are chemistry, electronics and beverages. In contrast to that machinery, iron and steel, paper and board and construction are characterized by relatively high productivity mobility, irrespective of the choice of the mobility index. The remaining industries are in between with contradictory results from different mobility indices in some cases.

Table 2
Mobility Indices for Productivity Scores

Industry	M_B	M_U	M_P	M_E	M_2	M_D	*#Firms*
Chemistry	0.27	0.34	0.35	0.35	0.11	0.77	52
Electronics	0.29	0.35	0.35	0.35	0.18	0.76	36
Precision Mechanics/Optics	0.27	0.27	0.68	0.65	0.33	0.99	11
Plastics and Rubber	0.38	0.46	0.47	0.47	0.20	0.91	21
Machinery	0.49	0.55	0.55	0.55	0.30	0.93	83
Automobiles	0.29	0.35	0.64	0.64	0.23	1.00	15
Iron and Steel	0.47	0.54	0.59	0.59	0.25	0.99	37
Paper and Board	0.44	0.41	0.66	0.63	0.24	0.99	13
Construction	0.75	0.69	0.76	0.76	0.42	1.00	22
Beverages	0.27	0.32	0.40	0.40	0.12	0.84	62
Textiles	0.32	0.39	0.40	0.40	0.15	0.83	40

Turning to the results for the output shares in table 3 we also find a similar agreement between the different mobility indices with respect to the ranking of the industries. Here plastics and rubber, machinery, paper and board and construction are the industries with the largest amount of mobility. At the lower end we find chemistry, electronics, precision mechanics/optics and beverages which are quite immobile although we have to admit that the mobility differences across industries are substantially lower than they are in the case of the productivity scores.

Table 3
Mobility Indices for Normalized Output Shares

Industry	M_B	M_U	M_P	M_E	M_2	M_D	*#Firms*
Chemistry	0.05	0.07	0.09	0.09	0.04	0.24	52
Electronics	0.03	0.04	0.08	0.08	0.02	0.24	36
Precision Mechanics/Optics	0.07	0.09	0.12	0.12	0.02	0.33	11
Plastics and Rubber	0.14	0.17	0.17	0.17	0.07	0.44	21
Machinery	0.12	0.16	0.16	0.16	0.05	0.42	83
Automobiles	0.08	0.11	0.16	0.16	0.03	0.43	15
Iron and Steel	0.11	0.15	0.15	0.15	0.05	0.40	37
Paper and Board	0.05	0.07	0.13	0.13	0.02	0.36	13
Construction	0.08	0.09	0.13	0.13	0.04	0.35	22
Beverages	0.07	0.09	0.10	0.10	0.02	0.27	62
Textiles	0.10	0.13	0.17	0.17	0.04	0.43	40

To provide further evidence in favor of the central message of this paper it is essential to compare the magnitudes of the mobility indices in the two tables above. Doing this we find that each single entry in table 2 for the productivity scores is at least twice as high as each single entry in table 3 for the output shares. So, here again mobility is much higher in the case of the productivity scores than it is in the case of the output shares and therefore our findings for the mobility indices are totally consistent with the results of the Salter curves and with Geroski's (1998) two stylized facts mentioned above.

The calculations of the mobility indices are robust in various respects. First, results obtained using a five-state Markov chain instead of the four-state chain show no qualitative differences. Second, using a fractile Markov chain where the states are determined separalety in every period according to the rule we employed for the initial period (see Quah 1996, pp.

150f.) even strengthens the central result of a much larger magnitude of mobility in productivity scores as compared to mobility in output shares. Third, using labor productivity instead of total factor productivity againt leads – with one exception – to the same conclusion.

5. Interpretation and Further Research

To summarize, using two different approaches we have found a pattern of a much higher technological mobility (measured by the mobility of total factor productivity scores) as compared to economic mobility (measured by the mobility of output shares normalized by maximum output share in the respective industry) that is consistent across the large quoted firms of eleven industries of the German manufacturing sector.

Two opposing forces are working with respect to technological mobility. On the one hand we have the notion of success-breeds-success which implies a low degree of mobility. On the other hand we have the notion of catching-up fuelled by the exploitation of advantages of relative backwardness and the notions of falling behind and of leapfrogging whose effects point to a high degree of mobility. Thus, if we interpret technological mobility as the result of the differential success of firms in the implementation of technological innovations our findings suggest that the tendency towards success-breeds-success is dominated by the other forces that promote turbulence with respect to productivity. With respect to economic mobility we can hypothesize mobility-hampering effects of the success-breeds-success phenomenon, possibly supported by the working of dynamic economies of scale, and mobility-enhancing effects of market competition. Here we find a domination by the former bunch of forces.

Equally interesting is a classification of industries according to increasing/decreasing technological and economic heterogeneity based on the Salter curves. Although at the present stage of our analysis this is rather tentative, we can identify precision mechanics/optics automobiles and construction as industries characterized by decreasing economic as well as technological heterogeneity. At the other extreme chemistry, electronics and textiles can be identified as industries in which both economic and technological heterogeneity are increasing. The mixed cases comprise machinery, plastics and rubber and iron and steel with increasing economic heterogeneity and decreasing technological heterogeneity and paper and board and beverages as cases with decreasing economic heterogeneity and increasing technological heterogeneity.

A theoretical model that has the potential to explain these differential dynamics of technological and economic heterogeneity is the replicator dynamics model (see Metcalfe 1994). So one promising avenue of further research is to integrate the purely empirical findings regarding mobility reported in this paper into the theoretical framework provided by the replicator dynamics model and its extensions. A second avenue of further research is to investigate the statistical significance of the results. Schluter (1998) provides the asymptotic distribution of the trace index M_P on which statistical tests can be based. In the present case of rather small samples the bootstrapping approach (see e.g. Efron and Tibshirani 1993) to statistical inference can be fruitful, especially if we want to test if mobility indices are significantly different from each other in a statistical sense. The differences between technological and economic mobility are quite accentuated so here the economic significance of the results seems to be obvious. However, the differences in technological or economic mobility between industries are not so marked so that a sharpening of the results through statistical tests would be valuable.

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