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U.S. Manufacturing Industries, 1958-1996

by

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Abstract:

The sources of aggregate productivity growth are explored using detailed data for four-digit U.S. manufacturing industries during 1958-96 and a decomposition formula which allows to quantify the contribution of structural change. Labor productivity as well as total factor productivity are considered and the aggregation is performed with either value-added or employment shares. It is shown that structural change generally works in favor of industries with increasing productivity. This effect is particularly strong in the years since 1990, in high-tech industries and in durable goods producing industries. The impact of the computer revolution can be clearly identified.

JEL classification: L16, O12, O33, L60

Keywords: aggregate productivity growth, structural change, manufacturing

1 Introduction

Aggregate productivity growth, say in an industry or a broader sector, can have a huge variety of sources. On the one hand, it may be fostered by the internal productivity growth within the firms that constitute an industry or by the internal productivity growth within the single industries that constitute a broadly defined sector such as manufacturing. This internal productivity growth is itself influenced by deeper factors like R&D, a better educated workforce or the other factors discussed in Bartelsman and Doms (2000) and Griliches (1995). On the other hand it is possible that aggregate productivity growth may also be stimulated by the pure effects of structural change leading to the reallocation of market shares from less productive entities to more productive entities even without any internal productivity growth. These contributions to aggregate productivity growth are caused by the process of competition leading to above-average growth (in terms of sales or employment) of technologically progressive firms or industries. In the case of firms a further source of aggregate productivity growth may be the exit of firms with below-average productivity performance and the entry of firms with above-average productivity performance. Of course, this latter source of aggregate productivity growth is absent if industries within a broader sector are considered.

In this paper, the aggregate productivity growth of the U.S. manufacturing sector during the period 1958-96 is investigated using a decomposition formula that permits the separation of the contributions of the internal sources of productivity growth of the more than 450 manufacturing industries at the four-digit level of aggregation from the external sources that are associated with structural change. Productivity is defined either as labor productivity or as total factor productivity, computed by a nonparametric approach. Structural change is defined either in terms of changing shares of the industries within total manufacturing value added or employment. Different time periods and industry subgroups are considered to gain a more complete picture of the sources of aggregate productivity growth.

The results show that even thought the internal productivity growth of the single industries dominates aggregate labor productivity growth, the effects of structural change in the form of reallocation of value added or employment towards industries with increasing productivity levels contribute considerably to aggregate labor productivity growth. In the case of aggregate total factor productivity growth, structural change is an even more important source of aggregate productivity growth. The effects of structural change tend to be larger if structural change is measured in terms of changing value-added shares than rather than changing employment shares. At the same time, structural change in terms of value-added reallocation across industries appears to be more intense than structural change in terms of employment reallocation. These results are in particular driven by the industry subgroups of the high-tech and durable goods producing industries. Furthermore, it can be demonstrated that the computer revolution is crucial for the association of productivity growth and structural change.

The paper proceeds as follows: Section 2 explains the ways used to compute labor and total factor productivity. This section also explains the formula used to decompose productivity growth to shed light on its sources. This is followed by the presentation of the results for labor productivity in section 3 and total factor productivity in section 4. The relation to results at higher or lower levels of aggregation reported elsewhere in the literature is discussed in the concluding section 5.

2 Productivity Measurement and Decomposition

2.1 Data and Labor Productivity

The data for the subsequent computations are all taken from the NBER-CES Manufacturing Industry Database, described in Bartelsman and Gray (1996). This unique database provides consistent annual time series over the period 1958-96 for quantity and price data of more than 450 manufacturing industries at the four-digit level of aggregation.[1] For each four-digit industry and each year, labor productivity is computed as the real value added divided by the total number of hours worked in the industry during a year. Since the number of hours worked is given only for the production workers in the data set, it is assumed that the non-production employees work the same number of hours as the production workers.[2]

[1] Used are data for 454 industries. Since the nonparametric productivity measurement described below requires strictly positive values for all inputs, five industries have to be excluded from the data base because a zero values for some inputs is computed in some years. These are the SICs 3292 (asbestos), 2384 (robes and dressing gowns), 2395 (pleating and stitching), 3713 (truck and bus bodies) and 3714 (motor vehicle parts and accessories).

[2] This can be precisely stated as (VADD/PISHIP)/(EMP·PRODH/PRODE) using the abbreviations given in the

2.2 Total Factor Productivity

For the computation of total factor productivity a nonparametric frontier function approach is applied. The specific method used here is the Andersen-Petersen variant of data envelopment analysis (Andersen and Petersen 1993). This is a nonparametric method that calculates an index of total factor productivity by the radial distance of the input-output combinations of the N industries towards a piece-wise linear frontier production function that is determined from quantity data alone without requiring assumptions about the specific form of the production function and without having to rely on price data. The Andersen-Petersen model calculates productivity by computing an index that indicates to which level the output of an industry has to be increased in order to reach a point on the frontier production function that is determined by the observations of the other $N-1$ industries in the sample, excluding the industry for which productivity is actually computed. Mathematically, the distance measure to the frontier of industry i in year t is the solution ϕ_{it} of the following linear programming problem

$$\max\left\{\phi_{it} : \phi_{it} y_{it} \leq \sum_{h\in\{1,\dots,N\}\backslash i} \lambda_h y_{ht} \; ; \sum_{h\in\{1,\dots,N\}\backslash i} \lambda_h \boldsymbol{x}_{ht} \leq \boldsymbol{x}_{it} \; ; \boldsymbol{\lambda}_{-i} \geq 0\right\}.$$

Here, y_{it} denotes the single output variable and $\boldsymbol{x}_{it}$ denotes the 6×1-vector of input variables of industry i in year t. $\boldsymbol{\lambda}_{-i}$ denotes the (N–1)-vector of weight factors λ_h, omitting the i-th element.[3] The solution of this linear program is denoted by ϕ_{it} and quantifies to which factor the output of industry i in year t has to be increased in order to reach a facet of the frontier function that is spanned by the observations of the other industries in the same year. Larger values of ϕ_{it} thus imply lower levels of productivity and therefore suggest to use the inverse as the measure of the level of total factor productivity subsequently, i.e. $a_{it} = 1/\phi_{it}$. Note that these productivity measures are always to be interpreted as relative toward the frontier function of the same year t and may therefore vary from year to year.

The data used to calculate the productivity scores are also taken from the NBER-CES manufacturing industry database. The nonparametric productivity measurement is performed

appendix of Bartelsman and Gray (1996).

3 This procedure is completely deterministic. An alternative econometric approach to the estimation of frontier functions promises to be able to separate measurement errors from the productivity measure (see e.g. Greene (1993)). Monte Carlo studies of Banker et al. (1993) and Ruggiero (1999), however, show that quite large samples are required for this advantage of the econometric approach to really show up.

using the real value of shipments [VSHIP/PISHIP] as the output variable.[4] The two labor input variables are the number of non-production workers [EMP–PRODE] and the production worker hours [PRODH]. Capital input is represented by the real equipment capital stock [EQUIP] and the real structures capital stock [PLANT], separately. Finally, the two variables that represent the input of materials and energy are the real cost of non-energy materials [(MATCOST/PIMAT)–(ENERGY/PIEN)] and the real expenditures on fuels and electricity [ENERGY/PIEN], respectively.

2.3 The Decomposition Formula

The research on the sources of aggregate productivity growth via the computation of productivity decompositions originates from empirical studies of entry, exit and growth dynamics at the level of firms and individual establishments (see Dunne et al. 1988, 1989 and Caves 1998). The empirical studies of Baily et al. (1992, 1996, 2001), Disney et al. (2003) and Foster et al. (1998) all use alternative descriptive decompositions of a share-weighted measure of aggregate productivity growth. The decompositions split productivity change into several terms, each with an illuminating economic interpretation.[5]

The decomposition formula proposed by Baily et al. (1996) that will be applied in this study is based on the share-weighted average productivity level $\bar{a}_t = \sum_{i=1}^{N} s_{it} a_{it}$. Herein, s_{it} denotes the share that industry i (out of a total of N industries) has in total employment or value added in period t and a_{it} denotes the productivity level of industry i in period t. The growth rate of aggregate productivity between periods t and $t+1$ is calculated as $(\bar{a}_{t+1} - \bar{a}_t)/\bar{a}_t = \Delta\bar{a}_{t+1}/\bar{a}_t$. Baily et al. (1996, p. 265) show that this growth rate can be decomposed according to[6]

$$\frac{\Delta\bar{a}_{t+1}}{\bar{a}_t} = \frac{\sum_{i=1}^{N} s_{it}\Delta a_{it+1}}{\bar{a}_t} + \frac{\sum_{i=1}^{N} \Delta s_{it+1}(a_{it} - \bar{a}_t)}{\bar{a}_t} + \frac{\sum_{i=1}^{N} \Delta s_{it+1}\Delta a_{it+1}}{\bar{a}_t}.$$

The first term on the right-hand side of the formula is interpreted as the *within effect*, which is the share-weighted average productivity growth of the individual industries. The second term represents the *between effect*. It is positive if industries with above-average productivity levels

[4] The abbreviations in square brackets are again those defined in the appendix of Bartelsman and Gray (1996).
[5] An antecedent to these productivity decompositions at the industry level is Salter (1960).
[6] The proof is very easy by suitably summarizing the terms in the numerators.

experience increasing shares between periods t and $t + 1$ on average, and industries with below-average productivity levels experience decreasing shares on average. The third term is a covariance-type term which is positive if industries with increasing productivity tend to gain in terms of their shares (or more general, if share change and productivity change tend to have the same sign). Consequently, this term is called the *covariance effect*. The between effect and the covariance effect together reflect the role of structural change in aggregate productivity growth.

In the literature, several modifications and extensions of this decomposition are discussed. Baily et al. (1992) and Foster et al. (1998) devise decomposition formulae with additional terms that represent the contributions of entering and exiting establishments to aggregate productivity growth. These effects are irrelevant for the investigation of inter-industrial structural change because of the constant industry coverage over the whole sample period. Griliches and Regev (1995) propose an alternative decomposition formula that is less sensitive to measurement error but allows no clear identification of the covariance effect, which is of special importance for the present study. Olley and Pakes (1996) decompose the share-weighted average productivity level into the sum of the equal-weighted average productivity and a term that is interpreted as the effect of reallocation from below-average productivity industries to above-average productivity industries. At the industry level, Fagerberg (2000) and Peneder (2003) employ a decomposition formula very similar to that of Baily et al. (1996), although with a slightly different interpretation of the between-industry effect.

3 Labor Productivity Growth

The following tables show the results of the application of the decomposition formula for labor as well as total factor productivity with either value-added or employment shares used for the aggregation. Each table contains the results for all industries over the entire sample period 1958-96 as well as for different subsamples of the data. The results reported in the tables refer to the periods indicated in the first column or to the entire period 1958-96 when certain industry subgroups are considered. Subperiods are defined by the years before and after the first oil crisis, 1958-73 and 1974-96, and, in addition, the period before the impact of the computer revolution becomes important, 1958-90. In each case, the period indices t and $t + 1$ in the decomposition formula are interpreted as referring to the industry means of the first and last five years of the respective period for both the real value-added shares and the productivity scores. This should render the results robust with respect to exceptional events in single years. For ease of comparison, the figures in the tables are each divided by the length of the respective time spans to which they refer.

Concerning subgroups, the four-digit manufacturing industries are divided into high-tech and low-tech industries according to the classification of Hadlock et al. (1991),[7] where a three-digit manufacturing industry group is classified as high-tech if the "industry's proportion of R&D employment in the year 1989 is at least equal to the average proportion for all industries surveyed" (Hadlock et al. 1991, p. 26) and as low-tech otherwise. Accordingly, high-tech industries in the present context are all four-digit industries that pertain to one of the three-digit industry groups classified as high-tech by Hadlock et al. (1991), while the remaining industries are classified as low-tech. This procedure results in subsamples of 34 high-tech and 106 low-tech three-digit industry groups to which 135 and 319 four-digit industries pertain, respectively. Another division of the four-digit industries is that into durable goods producing and nondurable goods producing industries according to the classification of the corresponding two-digit major groups listed in appendix B of Quah and Sargent (1993). This classification results in 258 four-digit industries producing durable goods and 196 four-digit industries producing nondurable goods. Other sample divisions distinguish between industries whose shares are increasing and industries whose shares are decreasing from the industry means of the first five years to that of the last five years of the respective sample period. The final investigation is concerned with the effect of excluding the seven exceptionally fast growing industries that are identified from the fractile transition matrix for the entire sample period in Krüger (2005). These industries managed to grow from the lowest (Q1) to the highest (Q5) quintile of all industries in terms of value-added shares. They are predominantly related to the computer revolution and are denoted by "Q1 $\rightarrow$ Q5" in the following tables.[8]

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[7] This classification has been frequently used in the recent empirical literature on the industry life cycle (see Agarwal (1996, 1998), Agarwal and Audretsch (2001) and Agarwal and Gort (1996), among others).

[8] These are diagnostic substances (SIC 2835), electronic computers (SIC 3571), computer storage devices (SIC 3572), computer peripheral equipment (SIC 3577), printed circuit boards (SIC 3672), semiconductors and related devices (SIC 3674) and electromedical equipment (SIC 3845).

Table 1
Decomposition of Labor Productivity Growth (Value-Added Shares)

subsample	N	productivity growth	within effect	between effect	covariance effect
period 1958-96	454	0.0630	0.0427	0.0006	0.0198
period 1958-90	454	0.0476	0.0389	0.0010	0.0078
period 1958-73	454	0.0398	0.0402	-0.0015	0.0012
period 1974-96	454	0.0517	0.0343	0.0017	0.0158
high-tech industries	135	0.0828	0.0565	-0.0012	0.0274
low-tech industries	319	0.0360	0.0327	0.0008	0.0025
durable goods industries	258	0.0675	0.0410	-0.0037	0.0302
nondurable goods industries	196	0.0585	0.0442	0.0042	0.0101
industries with increasing shares	198	0.0669	0.0524	-0.0018	0.0163
industries with decreasing shares	256	0.0369	0.0345	0.0008	0.0017
excluding Q1 $\rightarrow$ Q5	447	0.0497	0.0404	0.0017	0.0075

Note: the results are based on the changes between the averages of the first and the last five years of the indicated periods; N indicates the number of industries on which the respective results are based; the results for the industry subgroups are reported for the entire period 1958-96; the division of the industries in high- and low-tech is due to Hadlock et al. (1991) and the division into durable and nondurable goods producing industries follows Quah and Sargent (1993, appendix B).

3.1 Value-Added Shares

Considering first the case of labor productivity growth with value-added shares used for the aggregation, table 1 shows that results of the application of the decomposition formula to the different subsamples of the data. As the results in the first row of the table show, aggregate labor productivity has an average annual growth rate of 6.3 percent during the entire sample period 1958-96. This aggregate productivity growth is dominated by the within effect which explains about two thirds during 1958-96. The remaining third is explained by the positive covariance effect, implying that structural change is associated with productivity growth in a way that industries with increasing labor productivity also tend to gain in terms of value-added shares. The between effect appears to be nearly zero. The next rows show that this outcome is mainly driven by the development during the second subperiod 1974-96 and especially the years since 1990. Excluding the years 1991-96 lowers aggregate productivity growth and simultaneously lets the covariance effect drop by more than half in magnitude (comparing the first to the second row in the table).

During that period, information technology and computers became increasingly influential for all parts of economic life. In a related investigation at a higher level of aggregation, Jorgenson and Stiroh (1999) found that the computer revolution leads to a "massive substitution toward computers in both business and household sectors" (p. 113) during 1990-96 whereas both output and total factor productivity grew no faster than during 1973-90. Stiroh (2002) investigates those sources of the acceleration of aggregate U.S. (labor) productivity 1995-2000 compared to the earlier period 1987-95 which are related to the use and the production of information technology (IT) assets. He concludes that "IT-related industries are indeed driving the U.S. productivity revival" (Stiroh 2002, p. 1560). All these findings strongly support the exceptional growth performance of computer-related industries and their impact on productivity growth in the aggregate.

To shed more light on the sources of the development over the entire sample period, the sample is divided into several subsamples for which the decomposition is computed. Particularly relevant for productivity driven structural change implied by the large covariance effect for the whole sample of industries are high-tech industries and durable goods producing industries. These subgroups have faster aggregate productivity growth and much larger covariance effects than low-tech industries and nondurable goods producing industries. Counter to expectations, this outcome is not caused by an excessive overlap of durable goods producing and high-tech industries. Of the 258 durable goods producing industries, only 87 pertain to the subgroup of high-tech industries (compared to 171 pertaining to low-tech industries). The industries with increasing value-added shares show a large positive covariance effect, whereas the covariance effect in the industries with decreasing value-added shares is smaller by an order of magnitude. The latter industries aggregate productivity growth is almost exclusively due to the within effect. Finally, the exclusion of the seven exceptionally fast growing core computer industries weakens the covariance effect by a considerable amount, comparable in magnitude to the effect of excluding the years since 1990.

Table 2
Decomposition of Labor Productivity Growth (Employment Shares)

subsample	N	productivity growth	within effect	between effect	covariance effect
period 1958-96	454	0.0437	0.0406	-0.0007	0.0038
period 1958-90	454	0.0356	0.0360	-0.0008	0.0003
period 1958-73	454	0.0358	0.0374	-0.0012	-0.0005
period 1974-96	454	0.0342	0.0334	-0.0007	0.0016
high-tech industries	135	0.0663	0.0593	-0.0028	0.0098
low-tech industries	319	0.0290	0.0312	0.0001	-0.0023
durable goods industries	258	0.0450	0.0401	-0.0024	0.0072
nondurable goods industries	196	0.0420	0.0413	0.0014	-0.0007
industries with increasing shares	218	0.0429	0.0385	-0.0019	0.0063
industries with decreasing shares	236	0.0439	0.0419	0.0008	0.0012
excluding Q1 $\rightarrow$ Q5	447	0.0354	0.0377	-0.0002	-0.0020

Note: see table 1.

3.2 Employment Shares

Table 2 shows the corresponding results with employment shares used for the aggregation instead of the value-added shares. The overall pattern of the results is similar to the previous results with value-added shares. Exceptions are the facts that aggregate labor productivity growth appears to be lower for most subperiods and industry subgroups and that the contribution of the covariance effect is substantially attenuated and in some cases even becomes negative. Indeed, it appears to be the case that structural change in the manufacturing sector is more intense in terms of value added than in terms of employment. This can be seen if the average absolute cross-industry change of the respective shares is computed for each year. With a single exception, this magnitude is throughout higher for the value-added shares than for the employment shares. Other indicators such as the cross-industry standard deviations of the share change give a similar indication.

The essence of the discussion in this section is that the results provide an indication of a positive relation between differential productivity growth and structural change measured in terms of value-added shares (and less so in terms of employment shares). In the next section, the analysis is repeated for the nonparametrically calculated measure of total factor productivity and it is shown that the association of productivity growth and structural change is closer with this more sophisticated measure of technological change than it is with pure labor productivity change.

4 Total Factor Productivity Growth

4.1 Value-Added Shares

Looking at the results of the decomposition with value-added shares used for the aggregation in table 3, we find that the growth rates for total factor productivity appear to be much lower compared to the growth rates of labor productivity. This is on the one hand a straightforward impact of the increasing mechanization in most manufacturing industries, but is on the other hand also a result of the nonparametric method used here to compute total factor productivity. This method measures the total factor productivity of an industry in a specific year by the radial distance towards a piece-wise linear frontier production function determined by the best-practice observations of the same year. Thus, the productivity growth rates shown in this table and the next reflect only changes of the relative productivity positions of the industries towards this frontier function, but not changes of the frontier function itself. This meaning of the figures has to be kept in mind for the following interpretation of the results.[9]

[9] The alternative way of pooling all industries across all years together and computing a so-called all-time-best frontier function as in Cantner and Krüger (2006) leads to rather similar results. An even more sophisticated approach based on the Malmquist index as followed in Krüger (2004) can not be applied here since the Malmquist index only gives a measure of productivity change and does not allow to infer the associated productivity level measures which are required by the decomposition formula.

Table 3
Decomposition of Total Factor Productivity Growth (Value-Added Shares)

subsample	N	productivity growth	within effect	between effect	covariance effect
period 1958-96	454	0.0039	0.0002	-0.0001	0.0038
period 1958-90	454	0.0089	0.0071	0.0003	0.0015
period 1958-73	454	-0.0020	-0.0006	-0.0020	0.0007
period 1974-96	454	0.0068	0.0012	0.0014	0.0042
high-tech industries	135	0.0088	0.0025	-0.0007	0.0070
low-tech industries	319	-0.0006	-0.0012	0.0003	0.0003
durable goods industries	258	0.0085	0.0015	-0.0018	0.0088
nondurable goods industries	196	-0.0005	-0.0011	0.0015	-0.0008
industries with increasing shares	198	0.0056	0.0030	-0.0012	0.0038
industries with decreasing shares	256	-0.0023	-0.0019	-0.0001	-0.0003
excluding Q1 $\rightarrow$ Q5	447	0.0006	-0.0004	0.0008	0.0002

Note: see table 1.

Despite these lower aggregate productivity growth rates, the role of structural change appears to be more important for aggregate total factor productivity development over the entire sample period. In this case, the covariance effect explains nearly the whole change of aggregate total factor productivity, leaving only minor roles for the within and between effects. This implies that structural change also contributes considerably to aggregate total factor productivity growth in the manufacturing sector since, on average, industries with rising productivity also grow in terms of shares and industries with declining productivity also experience reductions of their shares. The between effect, however, appears not to be very important. Although nothing is said here about statistical significance, the interpretation suggested by this pattern of results is that productivity growth is positively related to share growth, whereas a once established productivity position above or below the average is rather unrelated to share growth. The first (productivity growth) effect outweighs the second (productivity level) effect. Thus, it is differential technological progress (mediated by productivity growth) which drives structural change in the first instance and not the relative productivity positions of the past.

Again the last six years of the sample period seems to play a special role for this outcome. Their exclusion leads to a dominating within effect instead of the covariance effect while the between effect remains small. In the years before the onset of the productivity slowdown the between effect is most important for the explanation of the decline of aggregate total factor productivity, implying that industries with below-average productivity levels experience increasing shares on average and vice-versa for industries with above-average productivity levels. In the following years the between effect weakens and the covariance effect is more important as a source of aggregate productivity growth.

As in the case of labor productivity before the results for the entire sample period are mainly driven by the subgroups of the high-tech industries, durable goods producing industries and the industries with increasing shares. This, together with the substantial weakening of the magnitude of the covariance effect once the years since 1990 are excluded, are further pieces of evidence to support the view that the computer revolution leads to widespread reallocation of value added across industries in favor of industries with rising total factor productivity leading to the strong positive covariance effect found here. Again, the exclusion of exceptionally fast growing industries reduces aggregate total factor productivity growth and the covariance effect to values close to zero.

4.2 Employment Shares

The results obtained using employment shares instead of value-added shares to aggregate total factor productivity are reported in table 4. Quite comparable to the differences between the results with value-added and employment shares in the case of labor productivity before, aggregate total factor productivity growth appears to be lower and the covariance effect is attenuated in magnitude. This is associated with the weaker appearance of structural change when measured in terms of employment shares. Notwithstanding this, the pattern of the covariance effect across different subperiods and subsamples is unaffected by the switch from value-added to employment shares.

Table 4
Decomposition of Total Factor Productivity Growth (Employment Shares)

subsample	*N*	productivity growth	within effect	between effect	covariance effect
period 1958-96	454	0.0011	0.0004	-0.0006	0.0013
period 1958-90	454	0.0077	0.0073	-0.0004	0.0008
period 1958-73	454	-0.0044	-0.0030	-0.0016	0.0003
period 1974-96	454	0.0043	0.0033	0.0002	0.0008
high-tech industries	135	0.0048	0.0028	-0.0013	0.0032
low-tech industries	319	-0.0006	-0.0006	-0.0003	0.0002
durable goods industries	258	0.0027	0.0007	-0.0005	0.0025
nondurable goods industries	196	-0.0005	0.0001	-0.0006	0.0000
industries with increasing shares	218	0.0009	-0.0007	-0.0012	0.0028
industries with decreasing shares	236	0.0009	0.0011	-0.0002	0.0000
excluding Q1 $\rightarrow$ Q5	447	-0.0006	-0.0003	-0.0003	-0.0001

Note: see table 1.

Thus, compared to the results for labor productivity the association of differential productivity growth and structural change appears to be stronger in the case of total factor productivity. Together with productivity growth within the industries, this covariance effect drives aggregate productivity growth of the manufacturing sector, whereas the contribution of the between effect is again small and negative in most of the subsamples considered. This outcome is mainly driven by the development since 1974 rather than before. For aggregate productivity growth as well as for the contribution of structural change the final six years of the sample period and the seven industries related to the computer revolution seem to be of particular importance. Regarding the industry subgroups, high-tech industries, durable goods producing industries and industries with growing value-added shares are much more crucial for the positive covariance effect and aggregate productivity growth than are low-tech industries, nondurable goods producing industries and industries with shrinking shares. In the latter subgroups the within effect (and sometimes the between effect) dominates aggregate productivity growth.

5 Discussion and Conclusion

Taken together, the results discussed above show four general features: First, labor productivity change is throughout positive and much higher than total factor productivity change, which is sometimes negative. The lower values for total factor productivity change may be due to increasing mechanization or to some extent caused by the nonparametric method used. Second, the within effect is the dominating component of the labor productivity decomposition, but is less important in the case of total factor productivity relative to the other components. Third, the between effect appears to be quantitatively unimportant. It also appears to be more frequently negative when employment shares instead of value-added shares are used for the aggregation. Fourth, the covariance effect is positive in most cases, especially when its contribution is large in magnitude. This confirms the theoretically plausible reallocation pattern of employment or value-added shares towards industries with increasing productivity levels. The covariance effect also represents a quantitatively more important contribution to total factor productivity growth compared to labor productivity growth.

Regarding subsamples, the association of productivity growth and structural change is particularly close for the entire sample period 1958-96 (where the years since 1990 seem to play a special role in driving this outcome), high-tech industries (rather than low-tech industries), durable goods producing industries (rather than nondurable goods producing industries) and industries with increasing shares (rather than industries with decreasing shares). The exclusion of seven exceptionally fast growing industries that are strongly related to the computer revolution weakens the covariance effect substantially. This, together with the special role played by the years since 1990 suggests a strong impact of the computer revolution on the process of structural change in favor of technologically progressive industries experiencing high rates of productivity growth.

Moreover, structural change is more intense when measured in terms of value-added shares rather than employment shares. Irrespective if productivity growth is measured using labor productivity or total factor productivity, aggregate productivity growth is considerably higher and the covariance effect is larger when value-added shares are used. In addition, technological progress measured by total factor productivity growth is more closely associated with structural change. Increases in labor productivity may also be due to rising degrees of mechanization of manufacturing production processes, but these appear to be also more closely associated with value-added reallocations than with labor force reallocations.

These findings are quite similar to related results regarding the effects of structural change among U.S. manufacturing establishments which are succinctly surveyed by Bartelsman and Doms (2000) and Haltiwanger (2000). Although the results vary considerably across time periods, data frequency, the specification of the shares in terms of labor or output, and the choice of labor productivity or total factor productivity, they can be summarized as follows. The within effect usually represents the largest contribution to aggregate productivity growth. The between effect is sometimes found to be quite small in absolute magnitude while the covariance effect is frequently positive and of considerable magnitude. Regarding entry and exit, the general pattern is that more productive entering establishments replace less productive exiting establishments. Overall, net entry contributes positively to aggregate productivity growth. Entering establishments are usually less productive than incumbents but experience considerable productivity growth upon survival. Comparisons of different time periods show that the contribution of reallocation to average productivity growth is higher during cyclical downturns.

Concerning studies for other countries, Cantner and Krüger (2006) investigate German manufacturing firms during 1981-98 with a decomposition formula and find a pattern rather similar to that for U.S. establishments. Especially after the German reunification the components referring to structural change and net entry are much more important than the within component. Disney et al. (2003) perform a similar productivity decomposition for of U.K. manufacturing establishments during 1980-92 to identify the contribution of internal restructuring (technological and organizational change among survivors) versus external restructuring (market share reallocations, entry and exit). The findings show that external restructuring accounts for about 50 percent of labor productivity growth and 80-90 percent of total factor productivity growth. A sizable contribution comes from entry and exit because entrants tend to be more productive than exitors. Much of this effect can be attributed to multi-establishment firms closing down poorly performing plants and opening new plants which operate at high productivity. External competition appears to be an important determinant of internal restructuring and productivity growth even if sample-selection issues are taken into account.

Haltiwanger (1997, 2000) emphasizes that structural change is much more intense within industries rather than between industries, even at the detailed four-digit level of disaggregation.[10] This may also be attributed to the quite short time spans used in the micro-economic studies. Over longer time spans such as used in the present study this finding may reverse. The widely evident turbulence at the level of firms and establishments also stands in contrast to the perception of inter-industrial structural change as a rather smooth process. There is no contradiction, however, as Schumpeter recognized long ago, when he wrote that "the development of whole industries might still be looked at as a continuous process, a comprehensive view 'ironing out' the discontinuities which occur in every single case" (Schumpeter 1928, p. 382).

At higher levels of aggregation than the four-digit level in this study the effects of structural change on aggregate productivity growth appear to be weaker. Applications of decomposition formulae to international industry-level data are reported in Fagerberg (2000) and Peneder (2003).[11] Fagerberg (2000) investigates a data set of 24 manufacturing industries in 39 countries during the period 1973-90. He finds that for most countries the within effect dominates average labor productivity development, whereas the between effect is not very important in quantitative terms. The covariance effect appears to be negative in most countries. He concludes that on average inter-industrial structural change has not contributed much to aggregate productivity growth. Only in countries with an increasing share of the electronics industry, productivity growth was noticeably higher.[12] In his sample of three-digit manufacturing industries in the countries of the European Union, Peneder (2003) finds only a

[10] A particularly striking fact is that during the 1970s and 80s about 10 percent of all manufacturing jobs in the U.S. were lost in each year and about the same number were created. Out of these, only 13 percent are associated with reallocations across four-digit industries (see Haltiwanger 1997, pp. 57f.). See also Davis et al. (1996) for related findings.

[11] The antecedent to these productivity decompositions at the industry-level, Salter (1960), finds that across 28 U.K. industries roughly at the two-digit level during 1924-48 the within-industry effect is about as large as the components of the labor productivity (output per head) decomposition that represent structural change. This effect of structural change is found to be considerably smaller in a comparable sample of U.S. industries.

[12] The magnitude of the effect exerted by the electronics industry is disputed by Carree (2003), however.

weak impact of structural change on aggregate labor productivity growth. There is no systematic tendency for labor force reallocation towards industries with high rates of productivity growth. The results for different industry groups are very heterogeneous and many effects cancel out in the aggregate.

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