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Structural change in U.S. manufacturing: Stationarity and intra-distributional changes

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Abstract

The distribution of the shares of the four-digit industries in U.S. total real manufacturing value added is found to be remarkably stable over the period 1958–1996. Structural change, however, takes place in the form of considerable intra-distributional changes.

Keywords: Structural change; Distribution dynamics; Manufacturing

JEL classification: L16; L60; C14

1. Introduction

Structural change in the economy implies that some sectors or industries grow faster than others in the long-run which leads to changes of the shares that these sectors or industries have in the total. Most of the empirical evidence on structural change is highly aggregate, however. Well established are the long-run shifts of the shares of the three main sectors of the private economy: agriculture, manufacturing and services (see e.g. Kuznets, 1966; Kongsamut et al., 2001). Harberger (1998) brings together widespread evidence on structural change at the firm and sectoral level and concludes that firms and sectors grow in

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unpredictable ways caused by a multitude of influences (like mushrooms) in contrast to growth at the same rate (like yeast) which precludes structural change. In his words, "the 'mushrooms' story prevails just as much among firms within an industry as it does among industries within a sector or broader aggregate" (Harberger, 1998, p. 11).

In this note we extend the research on structural change by taking a closer look at the changes of the real value added shares of U.S. manufacturing industries on the detailed four-digit (SIC) level of aggregation over the period 1958–1996. Methodologically, the distribution dynamics approach is applied which is particularly suited to the analysis of structural phenomena since it focuses on the heterogeneity within an aggregate and the change of this heterogeneity. As the results reported below show, the process of structural change within the U.S. manufacturing sector is well characterized by a specific notion of balancedness: that of a stationary distribution of the shares. Specifically, the empirical analysis of the industry shares in total manufacturing real value added shows that the shape of the density function is very stable over the period 1958–1996. Nevertheless, structural change takes place in the form of movements of industries within the distribution and these intra-distribution dynamics are demonstrated to be of a considerable magnitude.[1]

The note proceeds as follows: Section 2 contains the results of the shape dynamics in the form of kernel density estimates while Section 3 studies intra-distribution dynamics using estimates of a fractile Markov transition matrix and mobility indices. Section 4 discusses some implications of the results.

2. Shape dynamics

The structural composition of the U.S. manufacturing sector is quantified here by the shares of the four-digit industries in total real value added of the manufacturing sector. The data are taken from the NBER-CES manufacturing industry database which covers the period 1958–1996 for more than 450 four-digit (SIC) industries and is described in Bartelsman and Gray (1996). To estimate the shape of the density a kernel density estimator with a Gaussian kernel is used. The bandwidth parameter is determined by the Sheather–Jones method (Sheather and Jones, 1991) which proves to be the favorable choice in the comparison of Jones et al. (1996).

At first, the kernel density estimator is applied to the industry means of the first five years (1958–1962) and the last five years (1992–1996) of the logged value added shares. The averaging makes the estimates robust with respect to shocks that are specific to a single year and the application of the logarithm serves to avoid boundary biases of the kernel estimator (see Wand and Jones, 1995). Fig. 1 shows these estimates in the left panel by the dashed and solid lines, respectively.

The immediate impression is that the shape of the density of the averages is approximately the same in the first and last five years. This could imply that the distribution of the value added shares is stationary. To secure against the possibility of large changes of the shape of the distribution during the intermediate years, the densities for all years are plotted simultaneously in the right panel of Fig. 1. This plot shows that the approximate stability of the density is not the result of an accidental conformity of the

[1] This notion is used subsequently in accordance with the terminology of Quah (1996) and others.

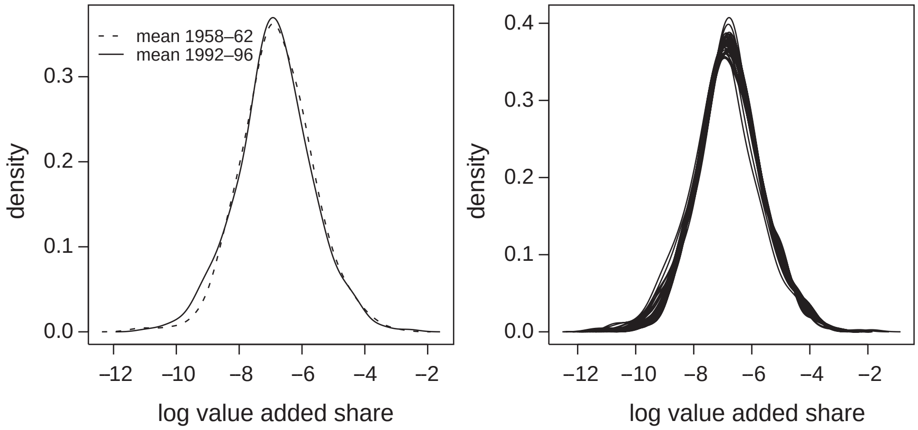

Fig. 1. Kernel estimates of shape dynamics.

distributions at the beginning and the end of the sample period but instead holds consistently during the entire sample period.

3. Intra-distribution dynamics

The stationarity of the shape of the distribution itself does not permit to draw conclusions regarding the intensity of structural change. The reason is that shape stationarity may be consistent with nearly constant shares of the industries as well as with substantial intra-distributional changes that compensate each other in a way that preserves the shape of the distribution. To get an impression of the intra-distribution dynamics, Table 1 shows the estimate of the transition matrix of a fractile Markov chain (see Quah, 1996).

The states, denoted by **Q**1,. . ., **Q**5, are defined by the quintiles of the means of the first (rows) and last (columns) five years of the sample, respectively, corresponding to the distributions in the left panel of Fig. 1. The entry in row i, column j of the table represents the fraction of industries that start in the ith quintile **Q**i and transit to the jth quintile **Q**j, with $i, j \in \{1,\ldots, 5\}$. In such a fractile Markov chain the industries are uniformly distributed across the states by definition of the quintiles. Thus, we investigate transitions from a uniform distribution to a uniform distribution and

Table 1
Transition matrix (fractile Markov chain)

	Q1	**Q**2	**Q**3	**Q**4	**Q**5
Q1	0.4778 (0.0464)	0.2333 (0.0440)	0.1333 (0.0339)	0.0778 (0.0258)	0.0778 (0.0293)
Q2	0.3297 (0.0466)	0.3516 (0.0492)	0.1978 (0.0404)	0.0769 (0.0297)	0.0440 (0.0223)
Q3	0.1648 (0.0403)	0.2088 (0.0452)	0.3187 (0.0468)	0.2308 (0.0418)	0.0769 (0.0280)
Q4	0.0110 (0.0137)	0.1868 (0.0405)	0.3077 (0.0441)	0.3516 (0.0489)	0.1429 (0.0379)
Q5	0.0110 (0.0104)	0.0220 (0.0175)	0.0440 (0.0249)	0.2637 (0.0401)	0.6593 (0.0422)

Estimates based on a fractile Markov chain; bootstrapped standard errors based on 1000 replications in parentheses.

Table 2
Mobility indices (fractile Markov chain)

	M_B	M_U	M_P	M_E	M_2	M_D
Index	0.8194 (0.0502)	0.7104 (0.0333)	0.7102 (0.0331)	0.7102 (0.0280)	0.3709 (0.0558)	0.9988 (0.0019)

The mobility indices are Bartholomew's index M_B, the unconditional probability of leaving the current state M_U, the trace index M_P, the eigenvalue index M_E, the second eigenvalue index M_2 and the determinant index M_D; the standard errors in parentheses below the mobility indices are based on the same 1000 bootstrap replications as those in Table 1.

by that are able to investigate intra-distribution dynamics in isolation while abstracting totally from shape dynamics. Reported in parentheses below the probability estimates are standard errors which are computed from 1000 replications of the pairs bootstrap which preserves the temporal dependence in the sample (see Biewen, 2002 for a discussion on the application of the bootstrap in the case of mobility indices).

The numbers on the main diagonal represent the probability of staying in the same quintile. These are the largest in magnitude in each row which points to a considerable role of persistence in share dynamics. Notwithstanding this persistence, the side diagonals are also occupied by non-negligible probabilities that indicate the propensity of transiting to the adjacent quintiles. As the standard errors show, most of them are quite precisely estimated. Even extreme transitions between the lowest and the highest quintiles can be observed.[2] In particular, seven industries in the sample (most of them related to the electronics revolution) start at the lowest quintile and transit to the highest quintile.[3]

The majority of industries changes the quintile during the period under investigation which is interpreted as an indication of considerable structural change. This is reinforced by the calculation of so-called mobility indices which are summary measures of the amount of intra-distributional changes. These mobility indices map the transition matrix into the interval [0,1], where the polar cases are zero, representing complete immobility, and unity, representing complete mobility. The results for the six variants of mobility indices proposed in Geweke et al. (1986) and Shorrocks (1978) are reported in Table 2. They are based on the transition matrix given in Table 1 and their standard errors have been computed simultaneously with the bootstrap replications for the standard errors there.

With the exception of M_2 these indices are closer to the upper bound of unity than to the lower bound of zero, pointing again to the presence of considerable intra-distributional changes. The standard errors assure that the mobility indices are all reasonably precisely estimated.

To supplement the above analyses, Table 3 gives an impression of the magnitudes of the changes. Most of the industries grow or shrink by less than a factor of two in terms of their value added shares. Nevertheless, there are about 30 industries which grow or shrink by more than a factor of four in terms of value added shares. These industries show dramatic growth or decline of their shares

[2] The equality of some of the probabilities in Table 1 is a pure coincidence caused by the same number of industries moving from Q1 to Q4 and Q5 and from Q4 and Q5 to Q1, respectively.

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

Table 3
Comparison of the means of the first and last five years

Interval	(0,0.25]	(0.25,0.5]	(0.5,1]	(1,2]	(2,4]	$(4,\infty)$
Number	30	73	175	107	40	29
Percent	6.61	16.08	38.55	23.57	8.81	6.39

Numbers are based on the industry means of the last five years (1992–1996) divided by the respective means of the first five years (1958–1962) of data available.

in total manufacturing value added which is a further sign of the significance of structural change in the process of industry evolution during the period under investigation.

4. Implications

To summarize, the statistical results reported in this note show that the process that governs the real value added shares of the four-digit industries in the U.S. manufacturing sector is associated with a stationary distribution together with substantial intra-distributional changes. These intra-distributional changes are the trace that the process of structural change leaves in the data. They constitute an important aspect that multi-sector growth models should address whose sectoral specification with emphasis on technological progress and monopolistic competition most closely resembles the characteristics of manufacturing industries.

The direct implications of the findings for the integration of structural change in growth theory are twofold. First, the stationarity of the share distribution justifies the construction of multi-sector growth models around ergodic processes and by that allows to draw on the wide variety of results established for this class of stochastic processes. Second, multi-sector growth models could be constructed that account for both features of the data, based on a stationary Markov process in discrete time or on stationary stochastic differential equations in continuous time.

However, this does not at all mean that growth models which focus on balanced growth paths on which the aggregate variables grow at the same constant rates are inappropriate. Empirically, balanced growth seems to be a valid approximation on the aggregate level for the U.S. economy.[4] That structural change is not necessarily in conflict with balanced growth at the aggregate level is theoretically shown in Kongsamut et al. (2001) and Meckl (2002), but it remains to be verified that this result holds beyond the particular specification of nonhomothetic consumer preferences that is presumed in these papers.

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[4] Fig. 1 of Jones (2002, p. 221) plots the time series of log U.S. GDP per capita over the period 1870–1994, which fluctuates remarkably close around a linear time trend with positive slope (with major exceptions during the years of the great depression and around the second world war).

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