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SOFT AND HARD WITHIN- AND BETWEEN-INDUSTRY CHANGES OF U.S. SKILL INTENSITY:

SHEDDING LIGHT ON WORKER'S INEQUALITY

by

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Abstract

In order to examine the worsening of inequality between workers of different skill levels over the past three decades and to further motivate the theoretical discussion on this issue, we use the decomposition methodology to focus on the *interaction* of within- and between-industry changes of the relative skill intensity in U.S. manufacturing. Unlike previous work, we use more detailed levels of industry classification (5-digit SIC product codes), and we analyze the impact of plants switching industries as well as of plant births and deaths on these changes. Internal, plant-level data from the U.S. Census Bureau's Longitudinal Research Database and the new Longitudinal Business Database provide us with the requisite information to conduct these studies. Finally, our empirical conclusions are discussed in relation to the inspired theoretical inference, as they enrich the debate concerning the sources of the inequality by justifying the skill-biased character of technical change.

Keywords: Skill Intensity, Skill-Biased Technical Change, Wage Inequality

JEL classification: F10. F16, E24, J21

* This paper is unofficial and has not undergone the review accorded official Census Bureau publications. The opinions and conclusions expressed in this paper are those of the authors and do not necessarily represent those of the U.S. Bureau of the Census.

1. Introduction

The worsening of inequality between workers of different skill levels for the past 30 years is an unquestionable fact[1]. In the frame of a standard argumentation, this occurrence could be seen as the price that has to be paid for the convergence of factor returns all around the world, yet UNCTAD (1997) demonstrates a generalized increase of income inequality in several countries, both developed and developing[2]. These sharply widening gaps would be less noteworthy if a sustained overall rising real wage accompanied them since, theoretically, efficient reallocation of production activities across the regions is supposed to increase real output of all countries that participate in a liberalized international economic environment, regardless of their initial position. Hence, effectively designed and applied redistribution mechanisms could then take everybody to a better position. Yet, does worsening inequality really occur in a growing economic environment? Real wages have fallen in the U.S. with a yearly average of about 0.4% since 1973 (Slaughter, 1998), and although Krueger (1997) is pretty much convinced of the improvement in living standards in developing countries, the picture that we get from several empirical contributions is not necessarily the same[3].

Contributions from the early 1990s regarding the deterioration in wages of the less skilled and/or of production workers mainly focused on the supply side of the labor market -- Murphy and Welch (1992) highlighted the significance of the aging of the baby boom, while others focused on the weakening of the unions and the relaxing of minimum wage regulations (Blackburn, Bloom, and Freeman 1990). Afterwards, acknowledgment of the simultaneous worsening of relative wages and relative employment drove the theoretical interests towards demand side explanations[4], with international trade and technology's evolution being the two main competitive arguments[5]. In the frame of this well-known debate, Berman, Bound, and Griliches (1994) used a decomposition equation in order to measure the share of overall change in relative skilled employment that occurred due to within- and between-industry changes at the 4-digit classification. Since they assume that within-industry changes arise because of skill-biased technical changes and since their estimates indicate that within-industry changes compose a significantly higher share of the total change, the authors concluded in favor of technology and against international trade as being the driving force behind these changes. Bernard and Jensen (1997) used a similar decomposition methodology. However, different from the Berman, Bound, and Griliches approach, they examine **plant-level data** for

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[1] Slaughter (1998) reports that the premium for male college-educated workers in the U.S. rose from 30% in 1979 to about 70% in 1995. Analogously, the employment of production workers in the British manufacturing sector fell between 1979 and 1992 by 41%, while the decrease for non-production workers was only 26% (Hine and Wright, 1998).

[2] Meckl and Weigert (2003), present a theoretical scenario, based on plausible assumptions, that links the final effect on relative wages also to individual decision making for acquiring human capital. Thereby, they show how the standard Stolper-Samuelson effect can be reversed in the case of developing countries.

[3] According to data presented by Streeten (1998) there was a steady decline in growth rates in several countries in the three decades after 1960. particularly for the OECD. As Rodriguez and Rodrik (1999) brought up, econometric studies focusing on the same period also show no robust relationship between growth and openness. But, with respect to absolute standards of living, Kaplinsky (2001) reports that between 1987 and 1998, a period of growing global integration, the number of people living below the poverty line remained almost unchanged. Moreover, it increased significantly in some regions, notably South Asia, sub-Saharan Africa, Europe and Central Asia (Poverty Reduction and the World Bank, 1996; Global Economic Prospects and the Developing Countries 2000.)

[4] Leuven, Oosterbeek and van Ophem (2004) support this diagnosis as they test for the consistency of wage differentials between skill groups across countries with demand and supply conditions. This specific framework does an even better job at explaining relative wages of low skilled workers. Similar are the conclusions of Hansson (2000), regarding the change in the share of skilled labor that increased steadily over the past 35 years in Swedish manufacturing. Especially for the period during the late 1980s and at the beginning of the 1990s, acceleration in the relative demand for skills appears to have propelled higher skill shares.

[5] Leamer (2000), Deardorff (2000) and Panagariya (2000), give a useful overview over the specific debate.

the U.S. manufacturing sector and conclude that increases in the skill intensity and the associated increases in the wage gap can be attributed substantially to international trade, or to be more precise, to changes in exporting establishments[6].

Yet, besides the question of the relative importance of within- and between-industry changes, there is a range of theoretical questions arising when we use the standard analytical tools. **First**, the Heckscher-Ohlin Model, although useful for defining the gains from trade and international specialization tendencies, has significant difficulties in explaining the simultaneous appearance of **three key observances** in the western economies: **a rising skill-premium**, along with **specialization tendencies toward more skill intensive production,** and a simultaneous generalized tendency of **increasing skill intensity in all branches**[7]. Restricted by the full-employment assumption, the standard approach denies the possibility of parallel within- and between-industry adjustments, regardless of which is the underlying reason, international trade or factor-biased technical changes (Zarotiadis, 2004b).

Second, the validity of the axiomatic technology-skill complementarity is debatable. In fact, the character of technological development was not always a skill-biased one. The evolution through the eighteenth century, from «artisanal shops» to the earliest factories, was characterized by a substitution of highly skilled individuals with physical capital and less skilled labor (Goldin and Katz, 1998). Acemoglu (1998) shares the same belief by saying «…new technologies are not complementary to skills by nature, but by design». In the same paper, as well as in Kiley (1999), technology's factor bias is being endogenized, as the response to the evolution of the region's relative factor abundance. Crifo-Tillet and Lehmann (2004) relax the assumption of single factor-bias of technology, but they take into account the factor intensity of the goods where technical change occurs. Wood (1994) goes even further by regarding defensive factor-biased innovation, as well as technical progress in general, partially as the response of domestic producers to increasing foreign competition[8].

The most recent theoretical contributions have concentrated on various arguments, trying to close the gap between standard economic theory and contemporary developments in the globalized economic environment. Following a similar approach that has been introduced in Zarotiadis (2004a), we calculate annual within- (WIC) and between-industry changes (BIC), yet we use plant-level data from the U.S. Census Bureau's Longitudinal Research Database and the new Longitudinal Business Database. Unlike previous work, we use more detailed levels of industry classification (5-digit SIC product codes), and we analyze the impact of plants switching industry as well as the impact of plant births and deaths on these changes.

The following section provides a more detailed explanation of the data and the methodology. Next, we discuss briefly the first striking result, which is the significant fall in the importance of WIC. Following, we present the results of applying our version of the decomposition equation, and we conclude after a brief theoretical argumentation.

2. Data and Methodology

This paper merges the U.S. Census Bureau's Longitudinal Research Database (LRD) with the Bureau's new Longitudinal Business Database (LBD). The LRD contains all the data collected for the Annual Survey of Manufactures (ASM, 1973-2001) and the Economic Census of Manufactures (CM, 1963, 1967-1997 collected quinquennally). Plants in the LRD have unique identifiers that allow them to be linked longitudinally. The LBD is derived from the Bureau's Business Register and contains basic information on an annual basis about the entire universe of legally operating establishments (i.e., a plant or a store) in the United States with at least one

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[6] More recent papers of Bernard and Jensen (2004a, b) appear to give updates of the previously mentioned work.

[7] See in Berman, Bound and Griliches (1994) and Francois and Nelson (1998) among others.

[8] A more detailed scenario about the "urge to survive argument" can be found in Zarotiadis (2004b).

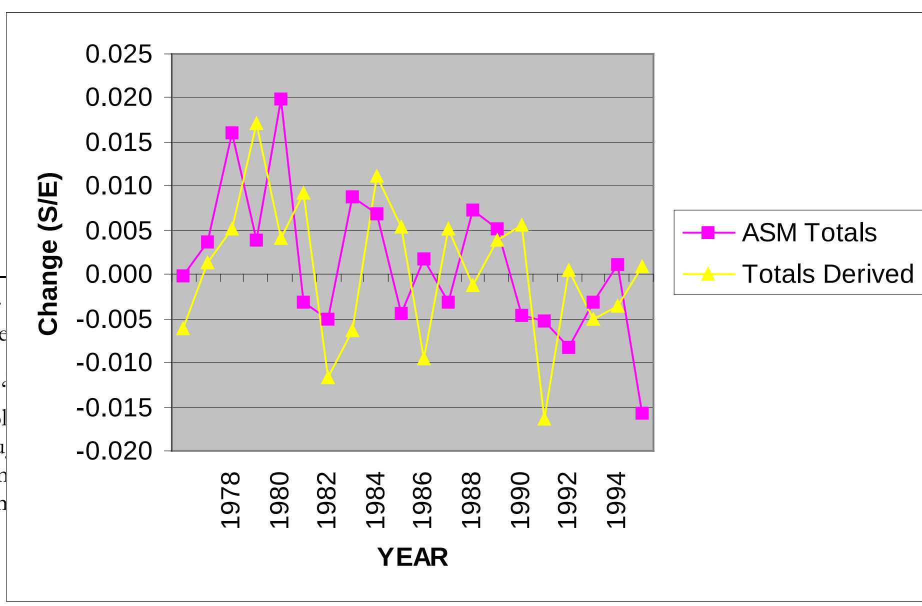
employee, for all industries.[9] The LBD also provides unique identifiers that link establishments over time and allows us to study, if not the entire life history of an establishment, at least a significant portion (from 1976-1999).

For the analyses in this paper, we use the LRD to obtain data about total employment, non-production workers, and production workers for each establishment and to classify each establishment using 5-digit SIC product codes rather than the typical 4-digit SIC code used for most publications. Each establishment is classified as follows: in both the ASM and the CM, establishments report revenues by product class code. For this paper, five-digit codes were assigned annually to the establishment based on the product for which the establishment had the most revenues in that year. Codes were assigned annually rather than for the entire life of the establishment to allow for industry switching. For 1973-1996, these are 1987 SIC product class codes, typically 5- or 7-digit.[10] In 1997, the Census Bureau converted to NAICS; therefore, for 1997 and thereafter, the LRD industry product codes use the NAICS system. It is beyond the scope of this project to convert the data to one standard. Further, given the nature of these analyses of within- and between-industry changes, it is important to have a degree of accuracy and standardization in the system being used. Hence, these analyses use data only for the years 1976-1996[11].

The Annual Survey of Manufactures is not designed as a continuous panel, and the sample of establishments is re-selected every 5 years. There are some establishments that are retained in the sample; however, these are typically only larger establishments (employment greater than 250). While these larger plants are responsible for a vast majority of total output, examining only these plants prevents us from examining changes where change is most likely to occur, in smaller establishments. Further, using only these larger establishments is likely to not provide an accurate picture of births and deaths of establishments. For these reasons, we matched establishment data in the LRD to the LBD data using unique identifiers in order to obtain birth and death information for the establishments in our sample. The establishment-level data were then aggregated to the 5-digit industry level (weighted to account for sampling in the ASM).

Summing up the figures for production and non-production employees over the whole of manufacturing, after we applied the above procedure, provides us with an estimated change in relative employment of non-production workers that lies very close to the aggregate data published by the ASM (see Diagram 1).

Diagram 1: Change in Relative Non-Production Employment (S/E) using published ASM totals vs. totals derived from our methodology[12]



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This convinces us that we do not bias in any way the underlying phenomenon, even after applying the presented methodology, which offers two basic advantages over previous work done in this area:

1) the use of more detailed industry codes in order to more closely examine "hidden" specialization tendencies without losing the usefulness of aggregating above the plant level (Zarotiadis 2004a), and
2) the examination of the impact of births and deaths on within- and between-industry changes.

Specifically, for each 5-digit industry over time, we sum separately total employment, number of production workers, and number of other employees[13]. This gives us an industry panel from which we can assess annual changes in skill intensity at the 5-digit industry level using the traditional decomposition methodology:

1. $$\Delta_t(S/E) = \Sigma[E_{i,t}/E_t - E_{i,t-1}/E_{t-1}](S_{i,t}/E_{i,t}) + \Sigma[S_{i,t}/E_{i,t} - S_{i,t-1}/E_{i,t-1}](E_{i,t-1}/E_{t-1})$$

This expression is simply the known decomposition equation (the 1st term is the between industry change, BIC, and the 2nd term the within industry change, WIC), derived for annual changes (Zarotiadis 2004a).

Further, these numbers are calculated annually for plants that survive, either in the same or in another industry, for newborn plants, and plants shutting down in each industry, enabling us to assess separately the impact of switching industry and the impact of births and deaths on the relative share of skilled employment through the following decomposition equation[14]:

2.
$$\begin{aligned}
\Delta_t(S/E) = \; & \Sigma[{}_tER_{i,t}/E_t - {}_{t-1}ER_{i,t}/E_{t-1}]\, S_{i,t}/E_{i,t} && \textit{“soft” BIC} \\
+ \; & \Sigma[{}_tEA_{i,t}/E_t - {}_{t-1}ED_{i,t}/E_{t-1}] S_{i,t}/E_{i,t} && \textit{“hard” BIC} \\
+ \; & \Sigma[{}_tEB_{i,t}/E_t - {}_{t-1}EC_{i,t}/E_{t-1}] S_{i,t}/E_{i,t} && \textit{“very hard” BIC} \\
+ \; & \Sigma[{}_tSR_{i,t}/E_{i,t} - {}_{t-1}SR_{i,t}/E_{i,t-1}] E_{i,t-1}/E_{t-1} && \textit{“soft” WIC} \\
+ \; & \Sigma[{}_tSA_{i,t}/E_{i,t} - {}_{t-1}SD_{i,t}/E_{i,t-1}] E_{i,t-1}/E_{t-1} && \textit{“hard” WIC} \\
+ \; & \Sigma[{}_tSB_{i,t}/E_{i,t} - {}_{t-1}SC_{i,t}/E_{i,t-1}] E_{i,t-1}/E_{t-1} && \textit{“very hard” WIC}
\end{aligned}$$

As one can easily see, the overall within- and between-industry changes are decomposed into three sub effects:

- Firstly, there is the change in total employment of the remaining plants (Remainers, R) in each industry, relative to manufacturing's overall employment, weighted by the industry's average skill intensity ($S_{i,t}/E_{i,t}$), thereafter *soft* BIC;
- Second, we have the change in industry's employment share due to the balance of plants that switch into the industry (Arrivers, A) minus those that exit into another industry (Departers, D), weighted also by the industry's average skill intensity, thereafter *hard* BIC;

[13] Like previous researchers we use non-production workers to represent skilled employment, and production workers to represent unskilled employees.
[14] In general, we do not have any data for a plant in the year in which it is considered a death. However, that fits exactly into the decomposition equation. For example, for firms that "die" in 1990. we calculate the number of skilled workers in 1989 that will lose their jobs in 1990 as a result of the death of the plant. See the appendix for a more detailed derivation of the 2nd equation.

- Third, there is the change in the industry's employment share due to the balance of newborn plants less closing plants (Births and Closers), multiplied again by $S_{i,t}/E_{i,t}$, thereafter *very hard* BIC.
- Analogously, we have the fist sub-effect of WIC, namely the change in relative skilled employment of the remaining plants in each industry, weighted by the industry's share in manufacturing's overall employment ($E_{i,t-1}/E_{t-1}$), thereafter *soft* WIC;
- Next, there is the change in an industry's relative skilled employment due to the balance of skilled employees of plants that switch into that industry minus those that exit into another industry, weighted also by the industry's share in manufacturing's overall employment, thereafter *hard* WIC;
- Finally, there is the change in the same industry's skilled employment due to the balance of skilled employees of newborn plants less closing plants, multiplied again by the industry's share in manufacturing's overall employment, thereafter *very hard* WIC.

After calculating the six different parts of overall annual change in manufacturing's skill intensity, we proceed with a discussion of the partial correlations searching for the direction and the causality among them.

3. Importance of Industry Aggregation

Before dividing WIC and BIC into the six aforementioned categories, however, we first want to take a look at the relative significance of WIC and BIC when we move from a less to a more detailed classification level. Berman, Bound, and Griliches (1994) as well as Zarotiadis (2004a) found that 4-digit within-industry changes of skill intensity accounted for the vast majority of overall change, at least during the 70's and the 80's. In the present paper we focus on a more recent period (1976-1996). Tables 1a and 1b give an overview of the decomposition by presenting the summarised WIC and BIC for the different sub-periods between 1976 and 1996, first at the 4- and next at the 5-digit classification level.[15]

Table 1a: BIC and WIC at the 4-digit classification

		1977-80	1981-85	1986-90	1991-96	**1977-1996**
WIC	Change of Relative Skilled Employment	0.0097	0.0121	0.0060	-0.0109	0.0169
	Share in Total Change in Relative Skilled Employment	*0.59*	*1,02*	*-20.01*	*0.58*	*1.84*
BIC	Change of Relative Skilled Employment	0.0068	-0.0002	-0.0063	-0.0080	-0.0077
	Share in Total Change in Relative Skilled Employment	*0.41*	*-0.02*	*21,01*	*0.42*	*-0.84*
Total Change in Relative Skilled Employment		0.0165	0.0119	-0.0003	-0.0189	0.0092

Table 1b: BIC and WIC at the 5-digit classification

		1977-80	1981-85	1986-90	1991-96	**1977-1996**
WIC	Change of Relative Skilled Employment	0.0126	0.0055	0.0064	-0.0127	0.0119
	Share in Total Change in Relative Skilled Employment	*0.73*	*0.83*	*1,74*	*0.71*	*1,23*
BIC	Change of Relative Skilled Employment	0.0047	0.0011	-0.0027	-0.0053	-0.0022
	Share in Total Change in Relative Skilled Employment	*0.27*	*0.17*	*-0.74*	*0.29*	*-0.23*
Total Change in Relative Skilled Employment		0.0173	0.0066	0.0037	-0.0179	0.0097

Using these sums, WIC *appears* to be far more significant in all four sub-periods, regardless of the classification we use. However, this simplified comparison (applied by Berman, Bound, and Griliches, 1994) could easily lead to wrong conclusions, especially in the case of our study since the sign of WIC and especially of BIC is not clearly positive. Diagrams 2 and 3 show us that although the variability of both series is of similar strength the values of BIC are more symmetrically located around zero than those of WIC. This is the main reason why the net sum of annual values of BIC is relatively lower than that of the same sum of the annual values

[15] The total change in relative skilled employment differs slightly at the 4- and 5-digit classification (0.0092 and 0.0097 respectively) since these are not exactly the same samples over time. Given that we are dealing with annual changes, we lose more industry observations at the 5-digit level than at the 4-digit level due to smaller sample sizes at the 5-digit level.

of WIC. An alternative way to evaluate the relative significance of the two adjustments should be to compare the sum of the ***absolute*** values of all annual changes (see Tables 2a and 2b). Doing that provides us with different figures -- in the case of the 4-digit classification, the sum of the absolute values of BIC is 82% of the same sum for WIC. Hence, the total amount of between-industry change is very close to the total amount of within-industry change even at the 4-digit level. The analogue figure when we decompose for the 5-digit classification increases up to 93.3%, which speaks to the increasing significance of the between-industry term.

Based on these estimates, using a more detailed level of industry classification enhances BIC, although modestly, since this absorbs part of the calculated, 4-digit, within-industry changes. As we work with less detailed classes of industries, specialization tendencies among subcategories within the same industry fall into the changes in the skill intensity of the wider industry. For example, enterprises that move within the broader industry category from producing relatively less skill-intensive to relatively more skill-intensive products (i.e., within-industry change). Expanding the level of classification enables us to account for this "hidden" between-industry change correctly.

Table 2a: Absolute Magnitude of BIC and WIC at the 4-digit classification

	1977-80	1981-85	1986-90	1991-96	**1977-1996**
$\Sigma\|WIC_t\|$	0.02086	0.01984	0.01546	0.01959	0.07575
$\Sigma\|BIC_t\|$	0.00763	0.02185	0.01800	0.01494	0.06241
$\Sigma\|BIC_t\|/\Sigma\|WIC_t\|$	0.366	1,101	1,164	0.763	**0.824**

Table 2b: Absolute Magnitude of BIC and WIC at the 5-digit classification

	1977-80	1981-85	1986-90	1991-96	**1977-1996**
$\Sigma\|WIC_t\|$	0.01887	0.01702	0.01578	0.02101	0.07267
$\Sigma\|BIC_t\|$	0.01092	0.02533	0.01570	0.01583	0.06778
$\Sigma\|BIC_t\|/\Sigma\|WIC_t\|$	0.579	1,488	0.995	0.754	**0.933**

4. Decomposing Changes in Skill Intensity

4.a Using the simple within- and between industry decomposition

Looking simply at the summarized WIC and BIC over the whole period could lead us to a second misinterpretation. The fact that they are of opposite sign (0.0119 and -0.0022 respectively in Table 1b) does not signify opposing directions of WIC and BIC. On the contrary, alone the picture in the following two diagrams shows a remarkable conformity among WIC and BIC. Besides restating the significance of WIC, Zarotiadis (2004a) refers also to the significant positive correlation among the annually estimated within- and between-industry changes. After denying alternative explanation scenarios, like the importance of business cycles and the hypothesis that BIC would result out of WIC, he concludes that either there is a defensive, by design, skill-biased technical change, or simply there is substantial hidden BIC in our WIC estimations, again for different reasons. The discussion in the previous section speaks for the validity of the simplest version of the hidden-BIC argument -- in less detailed classification levels, movements of plants to similar sub-industries of different skill intensity count as within-industry changes, although they are clear specialization tendencies. In other words, these are direct responses to the relative intensity of international competition[16].

Diagram 2: WIC and BIC at the 4-digit industry classification

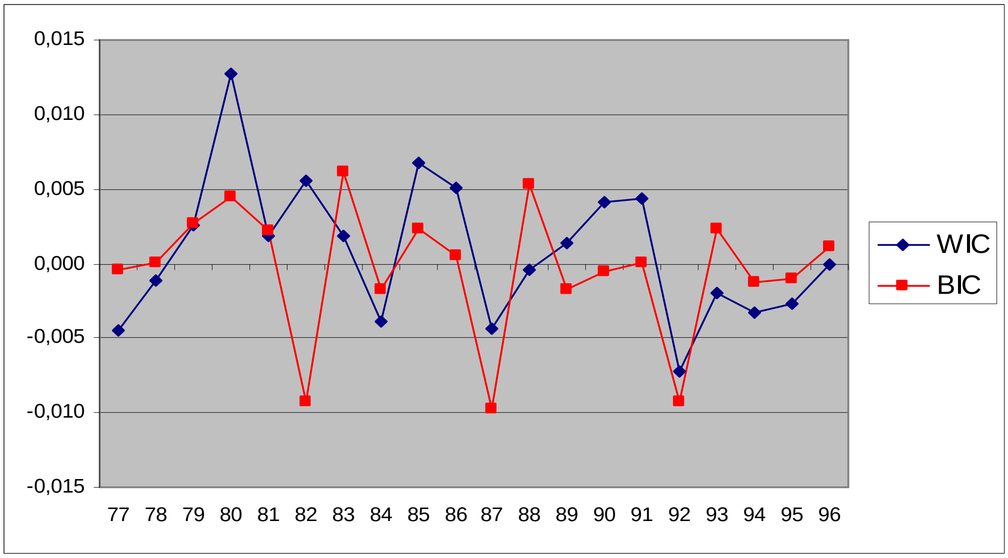
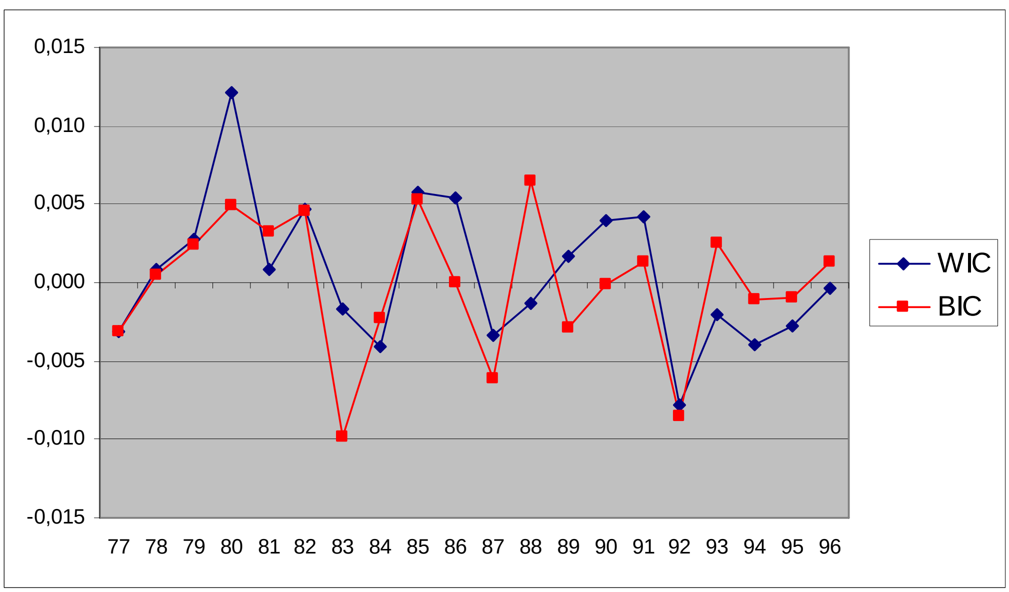


Diagram 3: WIC and BIC at the 5-digit industry classification



Nevertheless, although "hidden" specialization tendencies do exist, strong correlation among annual WIC and BIC remains even when we apply the first decomposition equation for

[16] "Hidden between-industry changes" could also result given that production can be fragmented into discrete activities with differences in the relative use of production factors. For example, enterprises could react to the increasing competition from low labor costs by transferring the relatively less skill-intensive activities abroad and concentrating on more sophisticated tasks domestically.

industries classified at the more detailed level! In fact, it becomes even stronger -- when we calculated annual WICs and BICs for 4-digit industries (Diagram 2), the positive correlation between these was 0.41, but it boosted up to 0.617 for the 5-digit classification (Diagram 3).

Business cycles might generate similar within- and between-industry changes (Zarotiadis 2004a) and could be the reason behind the computed positive correlation; however, the findings remain the same after we adjust for cyclical movements. Table 3 provides the results of estimating the partial correlations among BIC and WIC, at 4- and 5-digit classifications, computed through the partial coefficient of determination for holding the cyclical movements constant.[17]

Concluding from the above, the technically derived argument of "hidden" BIC is valid indeed, but it does not provide an explanation for the very "promising" paradoxical question of the significant conformity of WIC and BIC. Simple data limitations led in the past to an overestimation of WIC, but having roughly aggregated industries is definitely not the main reason behind the significant positive correlation of within- and between-industry changes of relative employment in our times. The discussion in the following section of the paper furthers this point.

4.b Accounting for Industry Changes – Births, Deaths, and Switchers

Perhaps the main contribution of the present paper is the introduction of a more detailed decomposition methodology (Equation **2**), which enables us to determine more than simply the share of the changes in relative employment that appears due to within- and between-industry changes. We actually analyze how much of the changes arise in the frame of "soft" developments, in the sense that plants remain in the same industry but reduce their total employment and change their skill intensity (soft BIC and soft WIC respectively), as opposed to harder and more "violent" adjustments where plants switch industries (hard BIC and WIC), or where closing plants are partially or fully displaced by newborn plants (very hard BIC and WIC). The appendix provides a more detailed presentation of deriving the second decomposition equation. The use of Equation **2** provides us with insights that boost dramatically the fascination of looking at the annual relation among within- and between-industry adjustments, and Diagram 4 gives a broad picture of the relationships among these six components.

Note that there are obvious, specific consistencies in the annual development of these six different parts. Breaking apart soft WIC and BIC, hard WIC and BIC and very hard WIC and BIC, Tables 4a-4c show strikingly similar patterns of these paired series.

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[17] To control for cyclical movements, we used annual percentage changes in manufacturing's overall revenues from the 1997 Economic Census, Manufacturing Subject Series, General Summary (Table 1-1a).

Table 3: Partial Correlations of BIC and WIC for steadily developed Revenues[18]

	Regression of WIC, SIC4 1977-1996		
	BIC	*%⊿(Revenues)*	*Constant*
Beta	0.53135	-0.05892	0.00426
Standard Error	*0.19369*	*0.02007*	*0.00139*
R^2(Y.xz)	0.4481		
R^2-adjusted	0.3832		
Beta		-0.04955	0.00355
Standard Error		*0.02308*	*0.00159*
R^2(Y.xz)	0.2038		
R^2-adjusted	0.1596		
	Partial Correlation		
r^2 (Y.xz)	0.3068		
r (Y.xz)	0.5539		

	Regression of WIC, SIC5 1977-1996		
	BIC	*%⊿(Revenues)*	*Constant*
Beta	-0.58963	-0.03063	0.00233
Standard Error	*0.18536*	*0.01901*	*0.00130*
R^2(Y.xz)	0.4625		
R^2-adjusted	0.3992		
Beta		-0.03989	0.00277
Standard Error		*0.02306*	*0.00159*
R^2(Y.xz)	0.1425		
R^2-adjusted	0.0949		
	Partial Correlation		
r^2 (Y.xz)	0.3732		
r (Y.xz)	0.6109		

[18] It should be noted that neither the coefficient estimations of the specific regressions, nor the R^2's are reliable. This is also the case for the calculated partial correlations, as BIC and percent change of revenues are not independent; hence, it is difficult to disentangle the effects. However, this numbers show the disappearance of the correlation among WIC and BIC as we move to less aggregated classification levels.

Diagram 4: Estimated BIC and WIC (Soft, Hard, and Very Hard), SIC5

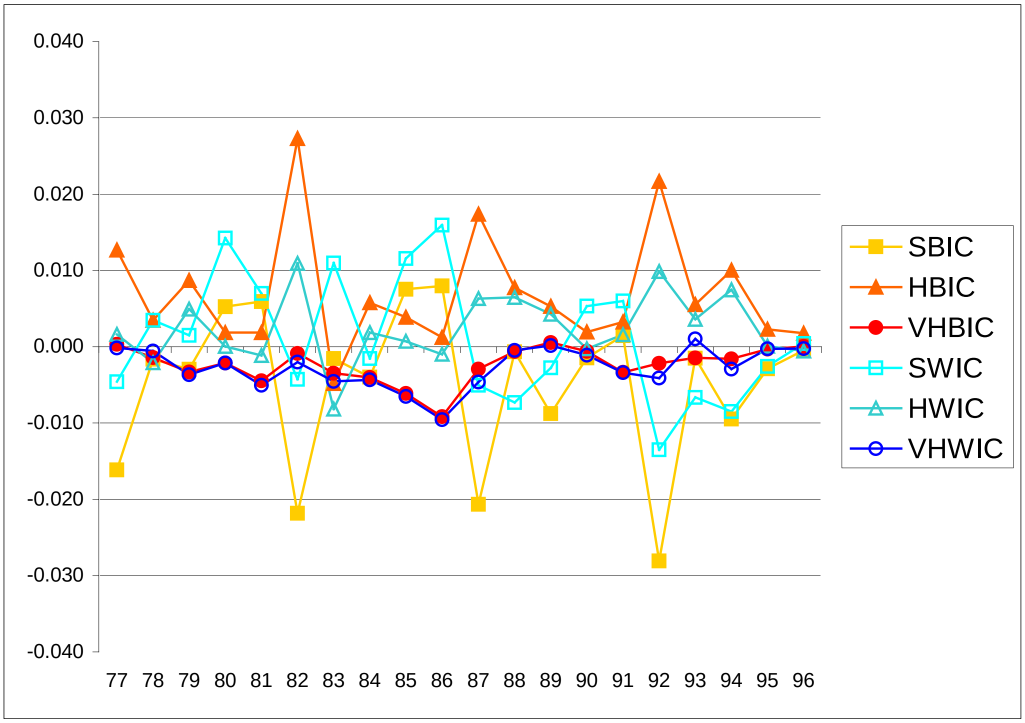


Diagram 4a: Estimated Soft BIC and Hard WIC, SIC5

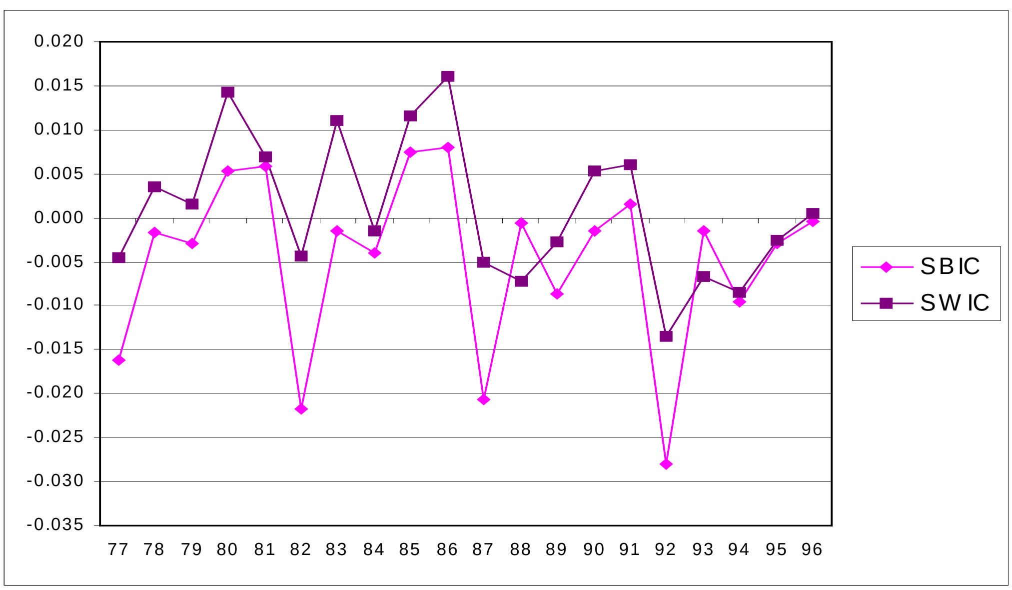


Diagram 4b: Estimated Hard BIC and Hard WIC, SIC5

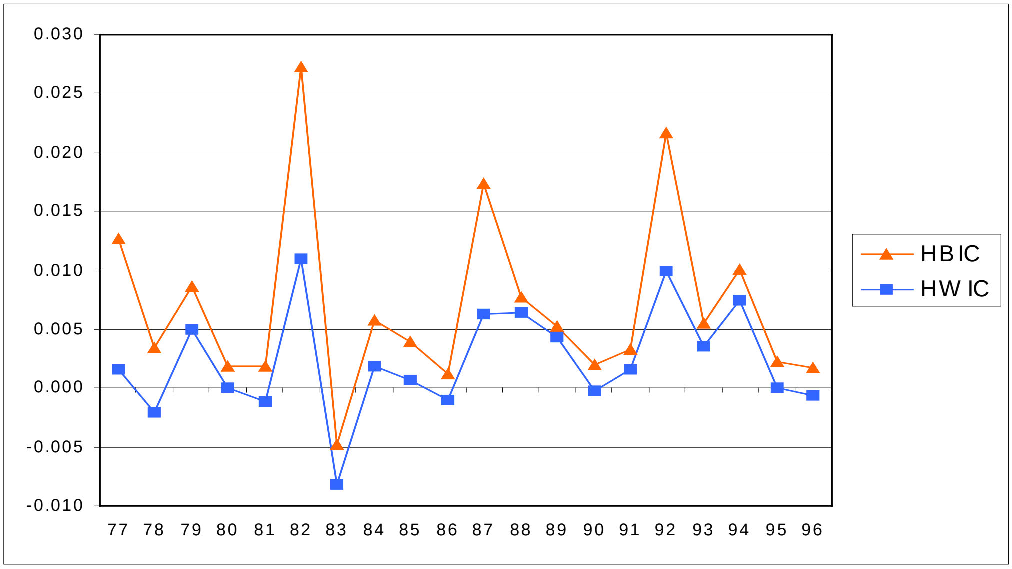
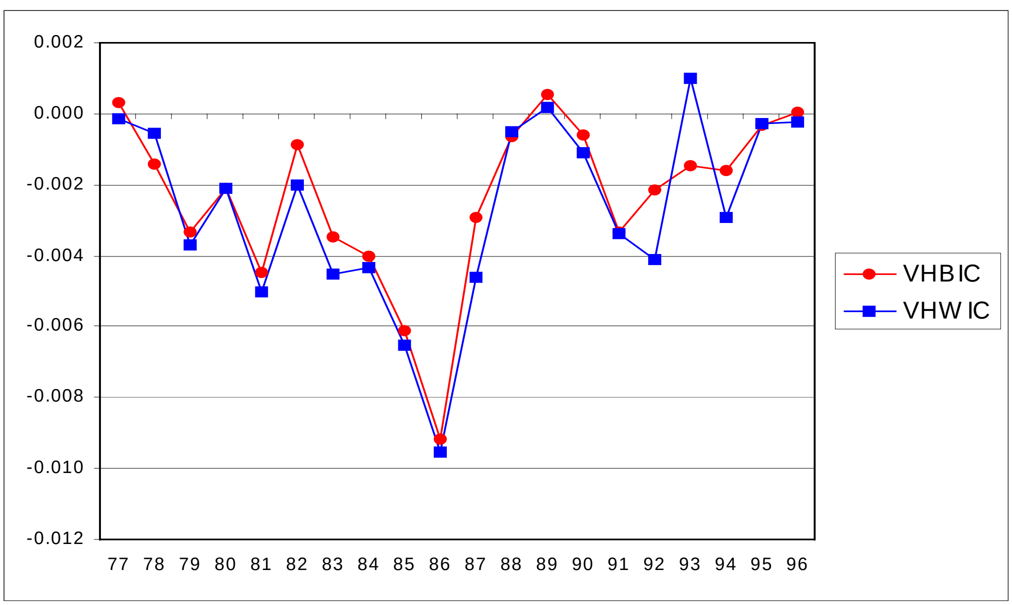


Diagram 4c: Estimated Very Hard BIC and Very Hard WIC, SIC5



As with Section 3, we present results for the summation of the actual values for these six types of changes over various periods between 1976 and 1996 and contrast these with results based on summations of the *absolute* values. This allows us to show the direction as well the relative magnitude of these changes. Table 4a provides us with the estimated effects for the actual values (both negative and positive), and Table 4b provides us with similar results using the absolute values.

From Table 4a, we can see that the soft and very hard adjustments offset the hard adjustments in each of the time periods. Hence, while the total change in relative employment seems to hover around zero, the magnitudes of the components of these changes are quite large. Further, Table 4a shows the soft adjustments to be the smallest of the changes relative to the hard and very hard adjustments, but when looking at the sum of the absolute values in Table 4b, we can see that the actual magnitudes of the soft adjustments (0.2834 from 1976-1996) is approximately 87% of the sum of hard and very hard WIC and BIC combined (0.3272). In terms of total magnitude, then, the very hard adjustments (those due to replacing closing plants with newborn plants) have the smallest values. Diagrams 4a-4c illustrate these points nicely. Finally, 4b shows that BIC is at least as important or even more important than WIC in all the categories.

Table 4a: Soft, hard and very-hard BIC and WIC, 5-digit classification

		1977-80	1981-85	1986-90	1991-96	**1977-1996**
Soft BIC	Change of Relative Skilled Employment	-0.0155	-0.0139	-0.0235	-0.0410	-0.0938
Soft WIC	Change of Relative Skilled Employment	0.0147	0.0237	0.0062	-0.0248	0.0199
Total Soft Adjustment	Change of Relative Skilled Employment	**-0.0008**	**0.0098**	**-0.0173**	**-0.0657**	**-0.0740**
	Share in Total Change	***-0.05***	***1,48***	***-4.70***	***3.66***	***-7.64***
Hard BIC	Change of Relative Skilled Employment	0.0267	0.0340	0.0335	0.0445	0.1387
Hard WIC	Change of Relative Skilled Employment	0.0045	0.0042	0.0158	0.0220	0.0465
Total Hard Adjustment	Change of Relative Skilled Employment	**0.0311**	**0.0382**	**0.0494**	**0.0666**	**0.1852**
	Share in Total Change	***1.80***	***5.76***	***13.44***	***-3.71***	***19.15***
Very Hard BIC	Change of Relative Skilled Employment	-0.0065	-0.0189	-0.0128	-0.0088	-0.0471
Very Hard WIC	Change of Relative Skilled Employment	-0.0065	-0.0224	-0.0156	-0.0099	-0.0545
Total Very Hard Adjustment	Change of Relative Skilled Employment	**-0.0130**	**-0.0414**	**-0.0284**	**-0.0188**	**-0.1016**
	Share in Total Change	***-0.75***	***-6.25***	***-7.73***	***1.05***	***-10.50***
Total Change in Relative Employment		0.0173	0.0066	0.0037	-0.0179	0.0097

Table 4b: Absolute Magnitude of BIC and WIC at the 5-digit classification

		1977-80	1981-85	1986-90	1991-96	**1977-1996**
Soft Adjustment	Total sum of absolute soft BIC	0.0260	0.0408	0.0395	0.0439	0.1502
	Total sum of absolute soft WIC	0.0238	0.0354	0.0364	0.0376	0.1332
	Soft BIC relative to Soft WIC	*1.0916*	*1.1534*	*1.0838*	*1.1677*	*1.1274*
Hard Adjustment	Total sum of absolute hard BIC	0.0267	0.0436	0.0335	0.0445	0.1484
	Total sum of absolute hard WIC	0.0087	0.0228	0.0183	0.0231	0.0730
	Hard BIC relative to Hard WIC	*3.0776*	*1.9110*	*1.8319*	*1.9243*	*2.0338*
Very Hard Adjustment	Total sum of absolute VH BIC	0.0072	0.0189	0.0139	0.0089	0.0489
	Total sum of absolute VH WIC	0.0065	0.0224	0.0159	0.0120	0.0569
	VH BIC relative to VH WIC	*1.1002*	*0.8446*	*0.8708*	*0.7476*	*0.8608*

For further examination of the relationships between these adjustments, Table 5 presents all the pair-wise estimated correlation coefficients among these six different components. The picture we get is even more convincing compared to the above diagrams and tables. The correlation among the between- and within-industry changes of the same character is surprisingly high: 0.764 between soft BIC and soft WIC and 0.877 between hard BIC and hard WIC. Moreover, annual *very hard* within- and between-industry adjustments seem to be almost identical. Their correlation comes up to 0.936. All these make the scenario of underlying forces that affect and/or generate between- and within-industry adjustments even more reasonable, since we could easily imagine that short-term strong specialization adjustments (in other words annual between-industry adjustments) appear due to developments in international competition or, more specifically, due to the urge to survive and deliberate, skill-biased technical adjustments.

Table 5: Correlations among the estimated soft, hard and very hard BIC and WIC[19]

	Soft BIC	Hard BIC	Very Hard BIC	Soft WIC	Hard WIC	Very Hard WIC
Soft BIC	1					
Hard BIC	-0.864	1				
Very Hard BIC	-0.441	0.240	1			
Soft WIC	**0.764**	-0.669	-0.609	1		
Hard WIC	-0.682	**0.877**	0.266	-0.737	1	
Very Hard WIC	-0.210	0.061	**0.936**	-0.504	0.139	1

Even more, Table 5 gives us another important insight -- soft and hard changes seem clearly to be substitutes of each other. In fact, we have significantly, negative correlations between soft adjustments on the one hand and the more "violent", hard and very hard corrections on the other. Logically, given the supposed exogenous pressures for adjusting

[19] The lower figures in each cell express the probability of getting a larger absolute value for the respective correlation.

to the forces of international competition, there is a trade-off of doing it in the soft or the hard way:

1) by adjusting the total and the relative employment of the existing plants in each industry,

2) by simply switching plant production into different industries, or

3) by shutting down and opening new plants.

Notice also that these trade-offs are suitable for explaining that the relation among overall BIC and WIC is indeed significant (discussed in Section **4.a** of the present paper and also by Zarotiadis 2004a), but of clearly lower degree than the positive correlations of Table 5. Using the second, more detailed decomposition methodology provides us with additional insights which strengthen even further the view that international competition lies behind between- and within-industry adjustments.

5. Conclusions

In the present paper, we made use of an exhaustive database with plant-level information from U.S. manufacturing. The methodology we used enabled us to utilize two advantages: more detailed levels of industry classification compared to the existing literature, and a more detailed decomposition equation. The first allows us to assess the importance of industry detail on the results. The second provides us with new insights into within- and between-industry adjustments of relative skill employment.

Previous findings of positive correlation among BIC and WIC could be at least partly justified by the "hidden" specialisation argument due to increased aggregation of industry classification. In fact, we were able to detect such a phenomenon, as the relative importance of between-industry adjustments increased when we used a 5-digit classification. Nevertheless, annual BICs and WICs remained highly related, with their correlation boosting up to 0.617.

In addition, as soon as we decompose WIC and BIC further, a hidden correlation is revealed: (1) soft adjustments, either within or between industries, appear simultaneously, and (2) hard within- and between-industry changes show the same patterns. The correlation is hidden in the sense that soft and hard adjustments are clearly substitutes of each other – a fact that leads to an underestimated positive correlation when we focus on total WIC and BIC.

As we could easily imagine that short-term, strong specialisation dynamics (i.e., annual between-industry adjustments) appear due to developments in international competition, one could argue for explanations based on the urge to survive and deliberately skill-biased technical adjustments. Therefore, the results and the respective analysis motivate further the theoretical discussion for the reasons lying behind the increasing inequality, especially in western economies.

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Appendix

Annual employment, total or skilled, of each industry can be further decomposed among:

- the employees that work this year in the remaining firms in this year, in other words, for the firms that exist in the certain industry in the present and the former year (${}_{t}e_{i,r,t}$ or ${}_{t}s_{i,r,t}$),
- the employees that work this year in the *newborn* firms that appear for the first time in that industry (${}_{t}e_{i,b,t}$ or ${}_{t}s_{i,b,t}$)
- and the employees that work this year in the firms (*arrivals*) that switched in that industry from another one (${}_{t}e_{i,a,t}$ or ${}_{t}s_{i,a,t}$).

Alternatively, skilled employment of each industry can be decomposed among:

- the employees that work this year in the firms that will remain into the following year, in other words, for the firms that exist in the certain industry in the present and the next year (${}_{t}e_{i,r,t+1}$ or ${}_{t}s_{i,r,t+1}$),
- the employees that work this year in the firms (*closing*) that will shut down in the following year (${}_{t}e_{i,c,t+1}$ or ${}_{t}s_{i,c,t+1}$)
- and the employees that work this year in the firms (*departures*) that will switch into another industry in the following year (${}_{t}e_{i,d,t+1}$ or ${}_{t}s_{i,d,t+1}$)[20]

Using the above breakdown and the related definitions, we can derive the following two identities:

A.1.a $E_{i,t} \equiv \sum_{r}^{R}({}_{t}e_{i,r,t}) + \sum_{b}^{B}({}_{t}e_{i,b,t}) + \sum_{a}^{A}({}_{t}e_{i,a,t})$… or simplified… $E_{i,t} \equiv {}_{t}ER_{i,t} + {}_{t}EB_{i,t} + {}_{t}EA_{i,t}$

A.1.b $E_{i,t-1} \equiv \sum_{r}^{R}({}_{t-1}e_{i,r,t}) + \sum_{c}^{C}({}_{t-1}e_{i,c,t}) + \sum_{d}^{D}({}_{t-1}e_{i,d,t})$…or simplified…$E_{i,t-1} \equiv {}_{t-1}ER_{i,t} + {}_{t-1}EC_{i,t} + {}_{t-1}ED_{i,t}$

A.2.a $S_{i,t} \equiv \sum_{r}^{R}({}_{t}s_{i,r,t}) + \sum_{b}^{B}({}_{t}s_{i,b,t}) + \sum_{a}^{A}({}_{t}s_{i,a,t})$… or simplified… $S_{i,t} \equiv {}_{t}SR_{i,t} + {}_{t}SB_{i,t} + {}_{t}SA_{i,t}$

A.2.b $S_{i,t-1} \equiv \sum_{r}^{R}({}_{t-1}s_{i,r,t}) + \sum_{c}^{C}({}_{t-1}s_{i,c,t}) + \sum_{d}^{D}({}_{t-1}s_{i,d,t})$… or simplified… $S_{i,t-1} \equiv {}_{t-1}SR_{i,t} + {}_{t-1}SC_{i,t} + {}_{t-1}SD_{i,t}$

Next, we can put the above identities in the equation that decomposes annual changes in manufacturing's relative skilled employment (or relative non-production employment) into WIC and BIC[21] (see equation **1** in the previous pages). After rearranging accordingly, we get an even more thorough and far-reaching decomposition that enables us to differentiate among six distinguishable terms:

[20] In the notation that we use, the left subscript shows the year in which employment is measured. On the other and, the right subscripts describe the firms: i shows the industry where they belong, r identifies the different remaining firms, b and a the new appeared firms due to new openings or to firms that switched from other industries, c and d disappearances due to shutting down or due to switching into another industry, and t expresses the year where the r-firms survived into (from t-1), or the year where the new-comers appear, or even the year of disappearance.

[21] Zarotiadis (2004a) provides a more detailed explanation of deriving the annually defined decomposition equation.

A.3 $\Delta_t(S/E) = \Sigma[{}_tER_{i,t}/E_t - {}_{t-1}ER_{i,t}/E_{t-1}]\, S_{i,t}/E_{i,t}$ *"soft" BIC*

$+ \Sigma[{}_tEA_{i,t}/E_t - {}_{t-1}ED_{i,t}/E_{t-1}]S_{i,t}/E_{i,t}$ *"hard" BIC*

$+ \Sigma[{}_tEB_{i,t}/E_t - {}_{t-1}EC_{i,t}/E_{t-1}]S_{i,t}/E_{i,t}$ *"very hard" BIC*

$+ \Sigma[{}_tSR_{i,t}/E_{i,t} - {}_{t-1}SR_{i,t}/E_{i,t-1}]E_{i,t-1}/E_{t-1}$ *"soft" WIC*

$+ \Sigma[{}_tSA_{i,t}/E_{i,t} - {}_{t-1}SA_{i,t}/E_{i,t-1}]E_{i,t-1}/E_{t-1}$ *"hard" WIC*

$+ \Sigma[{}_tSB_{i,t}/E_{i,t} - {}_{t-1}SC_{i,t}/E_{i,t-1}]E_{i,t-1}/E_{t-1}$ *"very hard" WIC*