The Role of Life Cycle Changes on Changes in Skill Intensity

T. Lynn Riggs*, Ioannis Theodosiou†, Grigoris Zarotiadis‡

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 have developed an improved decomposition methodology to better focus on the interaction of within- and between-industry changes of the relative skill intensity in U.S. manufacturing as well as various factors that influence these changes. This new decomposition methodology allows us to further examine changes in skill intensity by classifying plants annually into four categories: births, deaths, industry continuers, and industry switchers. In previous work, we find that there are offsetting changes amongst these groups for both within- and between-industry changes. In this paper, we analyze these relationships further using the NBER US Imports Data merged with internal, plant-level data from the U.S. Census Bureau's Longitudinal Research Database and the new Longitudinal Business Database. This further allows us to examine the impact of imports on changes in skill intensity within our subgroups. Using the internal Census data provides more detailed levels of industry classification (5-digit SIC product codes) than has been used in most previous work in this area. Finally, we examine whether regional variation is important. Our empirical conclusions are discussed in relation to the 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

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1. Introduction

One of the most recent debates in the economic literature is about the factors driving increasing wage inequality between employees of different skill levels while average real wages are stagnating. Although this is generally a macroeconomic problem, theoretical and empirical aggregations hide crucial aspects of these factors. In order to disentangle these effects, Berman, Bound, and Griliches (1994) introduced a decomposition equation that measured the share of overall changes in relative skilled employment that occurred due to within- and between-industry changes (WIC and BIC) using 4-digit industry classifications (based on SIC). Their supposition was that within-industry changes arise from skill-biased technical changes while between-industry changes are the result of specialization due to increased international competition. Using their decomposition equation, the authors found WIC to be much larger than BIC and hence concluded that technology is the driving force behind these changes.

In our previous work (Riggs and Zarotiadis 2006), we outlined two crucial misinterpretations related to the “decomposition methodology” used by BBG. First, when 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. By using more detailed industry codes from a 5-digit classification, we were able to uncover those “hidden” specialization tendencies without losing the usefulness of aggregation above the plant level. Further, we found significant conformity between WIC and BIC, which relates to the second problem of standard approaches in the literature—looking simply at summarized WIC and BIC over a wider period of many years could yield a completely untrue picture. In the case of our study with data from US manufacturing (Riggs and Zarotiadis 2006), there was a different sign in the within- and between-industry changes of relative skilled employment for the whole period 1977-1996 (0.0119 and -0.0022 respectively). Yet, despite the opposite signs of the overall sums, there is remarkable conformity between the annual WIC and BIC series, with a correlation between the series of approximately 0.6 for the 5-digit classification.

In the same study, we proceeded even further in exploring this significant link, as we decomposed the changes in relative skilled employment into three additional subcategories of within and between industry changes:

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1 Bernard and Jensen (1997) argued also about the same bias. They used a similar decomposition methodology, but, different from Berman, Bound, and Griliches, they examined plant-level data for the U.S. manufacturing sector and conclude that increases in 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. Bear in mind that more aggregated classifications bias these calculations in favor of within-industry changes while extremely low levels of aggregation, or applying these equations at the plant level, overestimates the between industry term.

2 A similar phenomenon is reported in Zarotiadis, 2004a.
1. “soft” adjustments due to changes in total employment and relative skill intensity changes of existing plants,
2. “harder” adjustments as a result of plants’ industry switching behavior,
3. even “harder” adjustments from newly opening and closing plants.⁴

Our findings were striking. The correlation between the WIC and BIC components of the same type (e.g., “soft” within-industry and “soft” between-industry changes in skill intensity levels of firms remaining in the industry) increased even more – this correlation was above 0.75 for changes that resulted from modifications in employment of remaining firms, and close to unity for those that were due to industry switching or opening and closing of plants. Moreover, within-industry changes in each of the different groups of plants were again significantly correlated (e.g., within-industry changes for remainers and for product switchers), yet with a negative sign. The same was true for between-industry changes. The offsetting effect of these changes also explains the lower, though significant, correlation among total within- and between-industry changes.

All these findings reveal a robust conformity in changes of manufacturing’s skill intensity that occur either because of interindustry specialization tendencies or because of intraindustry modifications of relative employment, accompanied by a clear trade-off between “soft” and “hard” adjustments. There are mainly two ways of explaining these observations theoretically. First, there could be a defensive, by design, skill-biased technical change, that links within-industry changes to international competition too. Wood (1994) was the first that spoke about defensive improvements of production’s technology as a response of western enterprises to pressure from less-developed countries. There is also some statistical support for “defensive innovation” in Sachs and Satz’s findings (1994) of faster total factor productivity growth during the 1980’s in low-skill-intensive manufacturing sectors, or in Lawrence and Slaughter’s (1993) and Leamer’s (1994) observations of higher productivity growth in low-skill rather than in high-skill sectors. In the present paper, we show that intensification in

⁴ In a way, we can think of this approach as a further breaking up of existing industry classification due to firms’ behavior. Although we concentrate in different attributes, the logic behind is similar to other papers that raised the question of why is an industry important for our empirical search and how should we use it. Bernard et al. (2003), for instance, argue that industry is not that informative about exporter status because it is a poor indicator of factor intensity. Taking both industry and factor intensity into account took them a bit further in explaining exporters’ productivity advantages. Also Schott (2003) applies an empirical methodology for recasting industry-level data into more theoretically appropriate “Heckscher-Ohlin aggregates”. When the model is reestimated using those aggregates, support for the idea that output is a function of endowments is strong.
the use of skilled employees is higher in relatively lower skill industries, which is much more direct evidence for a defensive, skill-biased technical change.

The second justification for the observances is simply that there is substantial hidden BIC in our WIC estimations, even when we move towards more detailed levels of industry classification. Firms could react to the increasing competition from countries with relatively cheaper unskilled employees by pushing the relatively less skill intensive activities abroad (through FDI or international cooperation and outsourcing) and concentrate on more sophisticated tasks.\(^5\)

Even so, revealing empirically the mentioned phenomenon forces us to make theoretical hypotheses but does not provide any direct evidence for either of them. At the same time, despite the conformity in the development of less or more wide-ranging aggregates through time, micro-level data uncovers new, sometimes confronting, stylized facts about the behaviour and relative performance of exporting firms, which hold consistently across a number of countries. Bernard et al. (2003) report for the US that exporters are in the minority (only 21\% of the plants in the Census report that they export goods while around two-thirds of them sell less than 10\% of their output abroad). However, exporting plants are much bigger than non-exporters and ship, on average, 5.6 times more than non-exporters. On the other hand, Mitchell (2005) reports an important inverse relationship between plant size and the skill premium in the long run. During the first half of the 20\(^{th}\) century, plant size rose and the skill premium fell, yet the opposite was true at the end of the century, meaning that skill premium changes could be connected to the organization of production.\(^6\)

Bernard et al. (2003), again, state that while previous work has sought to link trade orientation within industry, exporting producers are in fact quite spread out across industries. Despite that industry is a weak predictor of a plant's productivity performance, microdata bring out a striking association between these -- the productivity distribution of exporters is substantially shifted to the right of the distribution for non-exporters. As part of the same picture, Bernard and Jensen (2004) evaluated the different justifications for the volatile recovery of total US exports after 1987 (average annual increase of 10.3\% through 1992). Results from their analysis show also that industry, export-weighted, exchange rates; industry-level measures of foreign demand; and plant productivity play a role in the export increase. However, the productivity effect is relatively small. Furthermore, they report that the response of current exporters is substantially larger than that of other plants, suggesting that the combination of sunk costs and economy-wide events were the determining factors in shaping the export

\(^5\) Feenstra and Hanson (1999) elaborated and examined the outsourcing argument for the US.
\(^6\) Milgrom and Roberts' (1990) evidence that the recent development of U.S. manufacturing consists of adapting flexible, numerically controlled machines that allow plants to operate at a smaller scale, supports the Mitchell’s view: Production has shifted from traditional assembly line to batch processes using the new machines, integrated with computers to do a variety of tasks.
boom. While there has been an important increase in the numbers of plants exporting, by far the biggest increase in exports has come from existing exporters. Notice that this insight is highly related to our methodology of decomposing skill intensity changes among “soft” and “hard” adjustments.

In the present paper, we consider the particularities of the micro level, relating them to the broader phenomenon of parallel within- and between-industry changes as well as to reverse “soft” and “hard” adjustments. In so doing, we use industry rates of import penetration and exporting activities, intensity of skills and capital, profitability, as well as the regional distribution of economic activity. The paper proceeds as follows: first we present the exact methodology for the empirical research along with the data that we use, next we discuss the results and the statistical inferences and we interpret them in terms of the actual discussion regarding the sources of increased inequality, and last we conclude and proceed with proposals for enriching the theoretical debate.

2. Methodology and Data

Before we begin with presenting the methodology of the present empirical study, it is quite important to restate precisely the findings of our previous paper (Riggs and Zarotiadis, 2006) since they play a key role in the development of these analyses. In the second part of that paper, we decomposed the annual absolute changes in relative skilled employment of US manufacturing for the period 1976-1996, using a methodology that distinguishes where the change took place, within or between 5-digit industries, and if these changes occurred because of industry switching or because of births and deaths of plants. The following table illustrates more clearly the picture of this decomposition.

Table 1: Decomposition of manufacturing-wide changes in relative skilled employment

<table>
<thead>
<tr>
<th></th>
<th>Firms remaining within an industry (soft)</th>
<th>Firms switching industry (hard)</th>
<th>Balance of firms' births and deaths (very hard)</th>
</tr>
</thead>
<tbody>
<tr>
<td>Between Industry Changes</td>
<td>... changes in employment of remaining plants in industries of different average relative skill employment.</td>
<td>... employment of plants switching into an industry less the employment of those exiting from an industry of different average relative skill employment.</td>
<td>... employment of newborn plants less employment of those that closed in industries of different average relative skill employment.</td>
</tr>
<tr>
<td>Within Industry Changes</td>
<td>... changes in skilled employment of each remaining plant, weighted by the industry’s share in total employment.</td>
<td>... changes in skilled employment of plants switching into an industry less changes of those exiting from industries, weighted by the industry’s share in total employment.</td>
<td>... changes in skilled employment of newborn plants less changes of those that closed in each industry, weighted by the industry’s share in total employment.</td>
</tr>
</tbody>
</table>
The above table also simplifies the description of the main findings from our previous work. While we found an extremely strong positive correlation in the vertical sense in the above table (among within- and between industry changes of different types of plants), there was also a significant negative correlation in the horizontal sense among the different types of adjustments for each individual plant. In other words, we revealed a remarkable conformity in the development of different summations of individual decisions, made by each plant, with regard to their effects on overall relative skilled employment.

In the present paper, we take a step back in order to identify factors that drive the changes in the use of skilled versus unskilled labor over time among these different groups of plants. This should provide us with a better understanding of the underlying causes of the relationship between these very different macroeconomic trends regardless of individual firms’ microeconomic behavior that brings them about. At the same time, we will try to better understand each firm’s alternative reaction to better understand the trade-off between “soft” and “hard” adjustments.

There is in fact a range of different aspects in firms’ decision-making processes. First, there has to be a decision for opening a new plant. Next, as soon as a plant exists in a certain industry, it confronts continuously the choice to remain in that industry or to switch to another. Parallel to the switching decision, a plant also needs to assess whether or not to adjust its employment and/or to change its skill intensity (equivalent to a technological adjustment). Finally, each firm (to be more precise its investors) confronts continuously the option of shutting down each of its plants. Diagram 1 presents this decision-making process graphically and links each aspect to the appropriate adjustment of Table 1. The purpose of the present paper is to come across the factors that lie behind these decisions in order to justify the patterns of changes in skill intensity in production.

Based on the decomposition equation developed in our previous work (Riggs and Zarotiadis 2006), one can distinguish three different parts of the annual change in skill intensity of each 5-digit industry (notice the analogy to Table 1):

i. change in skilled employment of the remaining firms divided by the industry’s total employment: \[
\frac{(S_{i,r})_t - (S_{i,r})_{t-1}}{(E_i)_{t-1}}
\]

ii. skilled employment balance among firms switching into and those that exit (arrivals and departures), divided by the industry’s total employment: \[
\frac{(S_{i,a})_t - (S_{i,d})_{t-1}}{(E_i)_{t-1}}
\]

iii. skilled employment balance among new-born firms and those that closed in each industry, divided again by that industry’s total employment: \[
\frac{(S_{i,b})_t - (S_{i,c})_{t-1}}{(E_i)_{t-1}}
\]

Similarly, we distinguish three different parts of the annual change in the share of each industry in manufacturing’s total employment (in other words in each industry’s relative size):
iv. changes in employment of remaining firms of each industry divided by manufacturing’s total employment: 
\[
\frac{(E_{i,r})_t - (E_{i,r})_{t-1}}{(E)_{t-1}}
\]

v. employment balance among firms switching into and those that exit from each industry, divided by manufacturing’s total employment: 
\[
\frac{(E_{i,a})_t - (E_{i,d})_{t-1}}{(E)_{t-1}}
\]

vi. employment balance among new-born firms and those that closed in each industry, divided again by manufacturing’s total employment: 
\[
\frac{(E_{i,b})_t - (E_{i,c})_{t-1}}{(E)_{t-1}}
\]

**Diagram 1:** Firm’s Decision-Making Map with respect to our discussion of skill-intensity adjustments

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 employee, for all industries. The LBD also provides unique identifiers that link establishments over time and allows us to study, if not

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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. 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.

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).

After computing these six industry-specific measures, we end up having a panel of these six different time series for each 5-digit industry. The first three series correspond to the different decisions of firms that result in changes of skill intensity within each industry, while the second three correspond to the different decisions that induce a change in each industry’s relative significance (in terms of

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8 As part of the LRD management, the Census Bureau standardized industry codes to the 1987 classifications.

9 In "non-operating plants", all employment is non-production employment (e.g., central offices and auxiliary establishments). Non-operating plants are not included in the ASM or in CM (their employment is tracked through other sources); hence, these analyses focus only on operating manufacturing establishments.
shares in total manufacturing’s employment). Our intention is to explain the dynamics of these series by applying panel data techniques.

We will include the following explanatory variables in our analyses. First, we wish to consider regional characteristics and use the four regions as defined by the US Census Bureau: Northeast, Midwest, South, and West. Therefore, we classify the plants of our data set according to the wider region where they are located and calculate the percentage of each industry in each region.

We use import penetration rates and export intensities (value of imports and exports over the industry’s total value of shipments) in order to uncover the direct effects from foreign competition. Notice that both variables are defined at the level of 4-digit industries meaning that we have to adjust for aggregation bias. The value of imports and exports from each 4-digit industry were obtained from the NBER trade data set compiled by Feenstra and Schott.¹⁰

Next, we include five additional characteristics, namely the size and the skill intensity of the plant (measured as the absolute employment and the relative skilled employment respectively), capital intensity defined as the ratio of capital invested over total employment, as well as nominal returns on capital and labor (labor costs), measured as the ratio of value added minus labor costs over total capital invested and the ratio of labor costs over total employment respectively. We use this plant-specific information in order to get the respective characteristics for each 5-digit industry. So, we calculate the average size of plants belonging in a certain industry, the relative skilled employment and the capital intensity for the whole industry, as well as nominal returns on factors. In the case of skill intensity, rather than using relative skilled employment, which could cause problems due to the definition of our dependent variables, we consider the ranking of the industries according to this parameter. For that reason, we construct a ranking in the following way:

\[ \sigma_i = \frac{(s_i - s_l)}{(s_h - s_l)} \]

where \( s_i \) is the skill intensity of each industry, while \( s_l \) and \( s_h \) correspond to the lowest and highest measured skill-intensity, respectively.

Finally, we use the annual percentage change in total value of shipments for manufacturing to control for the business cycle.

The estimated coefficients that will result from the different models, as well as their significant differences will be discussed in relation to the collinear macroeconomic specialization tendencies and skill biased modifications of production, as well as to the trade off between “soft” and “hard” adjustments.

Finally, we will also apply the above procedures separately for a shorter sub-period, 1976-1990, since the tendency for skill intensity to increase is by far more evident in this part of the period that we consider. This can be seen in Diagram 2, which depicts the annual development of manufacturing’s relative

¹⁰ These data are available through the NBER website: www.nber.org/data/.
skilled employment, calculated with the published ASM totals vs. totals as well as with the figures derived from our methodology.\textsuperscript{11}

The following equation shows the basic equation that we modeled for these analyses:

\[ Y_{it} = B_0 + \sum B_i X_{i,t-1} + e_{it} \]

where \( Y \) represents one of our six series, \( i \) represents the industry, \( t \) represents the current time period, \( X \) is one of the explanatory variables measured for industry \( i \) in time, \( t-1 \). Given that our dependent variables are adjustments to industry condition, we hypothesize that the conditions in \( t-1 \) are relevant to driving these changes. Initially, we run these regressions using basic OLS; however, we also use various models which are appropriate for analyzing panel data (to adjust for heteroskedasticity and autocorrelation).

\textbf{Diagram 2:} Change in Manufacturing’s Relative Non-Production Employment (S/E) using published ASM totals vs. totals derived from our methodology\textsuperscript{12}

\begin{center}
\includegraphics[width=\textwidth]{diagram2.png}
\end{center}

\textbf{3. Empirical Results}

\textbf{3.1 Descriptive Statistics and Stylized Facts}

\footnote{11 We provided additional evidence that splitting the time period matters: Adding a dummy variable for the post-1990 period as highly significant (at the 1\% level) for all three of the measures of the changes in skilled employment. (Yet, it was not significant for and of the three measures of changes in employment.)}

\footnote{12 Employment figures were obtained from the 1997 Economic Census, Manufacturing Subject Series, General Summary (Table 1-1a).}
Before we proceed with the main part of our empirical analysis, it is important to focus on some descriptive statistical features of our sample of plants with regard to the explanatory variables that we will be using. On the one hand, this will reveal the main stylized facts that have been also emphasized in the existing literature. On the other, it will give us the relationships among our independent variables, which is important for setting our empirical model. Table A.1 in the appendix presents three different types of correlations: First, those being estimated out of the annual observations for each separate industry over the entire period (1976-1996) and second, in order to exclude the cross-time variation, the correlations among the different measures for each industry but only for two specific years in the beginning and at the end of the period: 1977 and 1995.

Results are not very surprising and they restate conclusions that have been already drawn in the existing literature. First, average labour costs (in other words labor’s remuneration) is higher the more skill intensive an industry is, typically because of the existing skill premium. The relationship reveals even stronger, when we exclude the cross time variation, coming up to over 0,40. In fact, supposing we assume a perfect interregional and interindustry mobility of labor, differences in an industry’s skill intensity is the main consistent reason for having different labor payments. Also average plant size and capital intensity of the industry is significant, with average labor’s remuneration being positively affected the bigger and the more capital intense production is. (Effects are increasing substantially when we focus only on cross-industry variation in 1977 and 1995).

The next important positive correlation is the one among export intensity and import penetration rates for the 4-digit industries (above 0,42). It seems that the more an industry exports, the higher is the part of the domestic relevant demand that is covered by imports. There are three main explanations for this observation. First, it shows simply the well documented and justified dominance of intraindustry trade among countries of similar characteristics. Second, it can also result from methodological issues, like the fact that the 4-digit classification is not detailed enough and keeps on classifying tradable against non-tradable goods together, or just the domination of the total value of each industry’s shipments. The fact that correlation falls notably (although it remains on significant levels) when we focus only on the cross-industry dimension, denotes after all that an important part of it is due to the cross time similar variation of exports and imports, following the economy-wide or industry specific incidents that affect the degree of openness.

Finally, we found modest but significant relationships, for instance the positive correlation among the export intensity and the industry’s skill intensity as well as the industry’s average labor payments. Both of them imply basically that US
export activity is stronger in the skill-intensifier sectors of productions. Further, we report significant negative links between the industry’s average return on capital on the one hand and capital intensity of production and labor payments on the other, yet only for the cross-industry dimension in 1977.

3.2 Regression Results and Significant Differences

As the above discussion revealed, average labor cost for each industry are highly correlated to the industry’s skill intensity as well as to the production’s size and capital intensity. In other words, three of our independent variables provide already significant and theoretically consistent information regarding average labor’s remuneration in each industry. Therefore, we run the regressions in two different versions, once with the whole set of independent variables (as presented above) and once after dropping out industry’s average labor costs.

Tables A.2 till A.5 in the Appendix presents the results of the different regressions in more details. The following tables give simply the significant signs that have been estimated in the six different series of independent variables that we developed for each industry. The picture helps us to discuss the main empirical observances, with respect to the specific questions that we set initially.

The first thing that someone needs to say about the estimated signs of the coefficients is that they are everywhere the same, regardless the period (1976-1996 or 1976-1990) and the set of explanatory variables that we use (with or without average labor’s remuneration). Further, it seems that regional features explain a significant part of the trade-off among soft and hard adjustments, especially for the within-industry changes. At the same time, the regenerated part of plants (employment balance of new-born minus closing firms) is higher in industries that are more concentrated in the Midwest and the South, which could be responsible, under specific conditions, for a significant part of the positive correlation of “very hard” BICs and WICs. Overall, one needs to take a closer look in the socio-economic features of the regions, because institutional aspects, differences in labor qualities, in financial opportunities or even in the degree of openness could be the reason.

Business cycle (% change of manufacturing’s annual value of shipments) provides also a considerable explanation for the trade-off among “soft” and “hard” adjustments, especially among adjustments in total and in skilled employment of the remainers on the one and the new-born minus the closing firms on the other. The first seem to behave in a counter-cyclical manner, while the second in a pro-cyclical one. In other words, opening of new and closing of old firms is for US manufacturing industries principally a way to adjust to the cyclical up- and downturns.

Looking at the different industries in 1977 provides us with slighter but still significant negative correlations among the same characteristics and import penetration rates.
Table 2: Signs of the significantly estimated coefficients

In the upper line we have the 1976-96 regressions while in the lower the regressions for the period 1976-1990. Left side gives the estimations with the whole set of Independent and right side those when we drop average labor costs.

<table>
<thead>
<tr>
<th>Changes in</th>
<th>Remainder’s Employment</th>
<th>Employment Balance of Switchers</th>
<th>Employment Balance of Births/Deaths</th>
<th>Remainder’s Skilled Employment</th>
<th>Skilled Employment Balance of Switchers</th>
<th>Skilled Employment Balance of Births and Deaths</th>
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<tr>
<td>Region 2</td>
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<td>Region 3</td>
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<td>Region 4</td>
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<td>Business Cycle (ΔTVS)</td>
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<td>Average Plant Size</td>
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<td>Export Intensity</td>
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<td>Import Penetration</td>
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<td>Skill Intensity Rank</td>
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<tr>
<td>Capital Intensity</td>
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<td>Returns on Capital</td>
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<td>-</td>
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<tr>
<td>Labor Costs</td>
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Next, let us take a closer look on the direct trade effects. Imports, although for the needs of this study they are defined at the 4-digit level, when we focus on the period 1976-1990, they have a marginally negative effect on each industry’s “very hard” employment adjustments and a clear positive effect on the adjustments of skilled employment in the remaining firms in that industry. Especially the last argument, is a very convincing indication for the defensive, deliberately skill-biased designed, technical changes, which are provoked by the intensity of international competition.
With exports, the picture is in some cases more bizarre: we see a clear opposite signed effects on “hard” and “very hard” changes in industry’s employment share, with employment changes due to switchers to be negatively affected and this due to the balance of new-born and closing plants to be positively affected by the industry’s export intensity. In other words, while the regenerated part of plants tends to move towards the intensively exporting branches, the opposite is true with the switchers, who show a clear back off the exporting activities.

Another observation which is difficult to assess is the clear negative sign of export intensity in an industry’s “hard” adjustments of skill intensity. In other words, the balance of skilled employment due to switchers in minus switchers out of an industry is more likely to be high in industries with less exporting intensity.

Following, it is interesting to assess the signs of the effects of the average plant size. First, it seems to provide good reasons for a positively correlated “soft” adjustment in the total and the skilled employment in each industry: the size (total employment) of the remainers is less likely to increase the higher their average size already is. At the same time, also their skilled employment adjustments are weaker in case we are dealing with large plants. Limited flexibility in association with production’s size is a good reason behind this observance.

Things look though quite different for switchers. Especially when we consider the whole period, they prefer to switch into industries with larger plants, in other words with higher-scale-productions. Also, there is modest evidence that they tend to increase the industry’s skill intensity, especially when they are switching into branches with larger productions. Probably, investing in new technologies which are more capital and skill intensive, may require an “economies of scale environment” in order to be worthy. Note however that this opposite effects on remainers and switchers is also a good reason behind the trade-off among “soft” and “hard” adjustments.

Next, another clear effect of the industry’s average plant size, is the clear negative sign for the employment adjustments that might occur due to new-born minus closing plants, which makes sense as entry and exit barriers are far more significant the larger is the required size of the plants.

Industry’s capital intensity is also quite significant, but it can only be used to explain the trade-off among “soft” and “very hard” within-industry changes. Capital intensity seems to strengthen the upwards adjustments of the remainers’ skill intensity, but, perhaps unexpectedly, it is negatively correlated to the increase in skill intensity that will results out of opening and closures of plants.

Moreover, switchers are clearly moving to industries with relative lower capital intensity, while at the same time, the remaining plants in industries that use relatively more capital are also less likely to increase their employment. Both
effects speak for a generalized specialization tendency for US manufacturing away from the capital intensive production during the specific period.

The skill intensity of the industries itself is also significant. It has a clear positive effect on the skilled employment adjustments of the remainers and also of the switchers: the more skill intensive an industry already is, the stronger is the increase of skilled employment in the remainers and, the more skilled employment will be generated due to the switchers. Arguments in the literature that speak how skilled employees adjust more efficiently to new technologies justify this observation.

Skill intensity ranking has further a significant positive impact on remainer’s employment, especially in the period 1976-1990, signifying the clear specialization tendency towards skill intensive productions.

Finally, also labor costs provide a clear support especially for the trade-off among “soft” and “very hard” adjustments.

... Furthermore, we can present tables analogue to the above that shows the significance of the differences in the estimated coefficients among the six dependent variables.

4. Conclusions and Theoretical Inferences

- Significant direct effects from trade on adjustments of size (total employment) and skill intensity.
- Regional characteristics and Business Cycles matter for both, the correlation of within- and between-industry changes, as well as for the trade-off among “soft” and “hard” adjustments.
- Industrial economics related arguments (plant size, capital and skill intensity etc.) seem to be also important for explaining this trade-off.
Literature


NorthSouth Institute, 1989, Trade, protectionism and industrial adjustment: three North American case studies, Ottawa


## Appendix

**Table A.1:** Estimated Pearson Correlation Coefficients among the industry characteristics and the respective Prob > |r| under H0: Rho=0  
(Observations: annual measures of the variables 5digit industries for 20 years)

<table>
<thead>
<tr>
<th>ave_te</th>
<th>ind_skill</th>
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<th>ind_ROL</th>
<th>ind_ROC</th>
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(Observations: measures of the variables 5digit industries in 1977)

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(Observations: measures of the variables 5digit industries in 1995)

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