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CHANGES IN THE DEMAND FOR SKILLED LABOR WITHIN U.S. MANUFACTURING INDUSTRIES: EVIDENCE FROM THE ANNUAL SURVEY OF MANUFACTURING

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ABSTRACT

This paper investigates the shift in demand towards skilled labor in U.S. manufacturing. Between 1979 and 1989, employment of production workers in manufacturing dropped by 2.2 million or 15 percent while employment of non-production workers rose by 3 percent. A decomposition of changing employment patterns in each of 450 industries reveals that the defense buildup and trade deficits can account for only a small part of the shift in demand towards non-production workers. We conclude that production labor-saving technological change is the most likely explanation for the shift in demand towards non-production workers since the shift is mostly due to changes in labor demand within industries rather than reallocation of employment towards industries with higher shares of skilled labor. Strong correlations between within-industry skill upgrading and both increased investment in computers on the one hand and increased investment in R&D on the other provide further evidence for production labor saving technological change.

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As has been well documented, skill differentials rose sharply over the 1980s. Current Population Survey (CPS) data show earnings differentials between high-school and college graduates rising more than 10 percentage points over the decade. Occupational differentials also rose. The Employment Cost index shows that between 1979 and 1989, the earnings differential between operatives on the one hand and managers and professionals on the other rose by roughly 10 percentage points, while the differential between laborers and operatives rose by roughly 4 percentage points. While the increase in skill differentials has been well documented (e.g., Murphy and Welch, 1989, 1992; Bound and Johnson, 1992; Katz and Murphy, 1992; Blackburn, Bloom and Freeman, 1990), there is no consensus as to its explanation. It seems evident that at least part of the widening of educational differentials can be attributed to a slowdown in the rate of growth of the college educated population accompanied by the continued growth in the demand for educated labor (Murphy and Welch, 1989; Katz and Revenga, 1989; Katz and Murphy, 1992), but this explanation fails to account for the sources of the growth in this demand.

Regarding the increase in the demand for college educated labor, a number of related questions deserve investigation: What are the sources of this increase in demand? Did the growth in demand for college educated labor accelerate during the 1980s? If so, was the acceleration something that we can expect to continue, as may be the case if the source were technological change, or was it a result of forces peculiar to the 1980s, such as the trade deficit, the deep recession or the military build up?

To date, most work done on the widening of skill differentials has used CPS data. While CPS data have the advantage of large sample sizes and detailed demographic information they contain no information on outputs or non-labor inputs. In the research reported here, we rely on data drawn from the Annual Survey of Manufacturing (ASM), 1959–1989, the Census of Manufacturing and the NBER trade data set to examine possible explanations for skill upgrading within U.S. manufacturing. We use information on other inputs and detailed classification of industries by output to evaluate alternative explanations for skill upgrading.

ASM data show dramatic changes within manufacturing in the nature of employment that are consistent with the CPS evidence on skill upgrading [Murphy and Welch, 1992]. In particular the ASM data reveal a trend decrease in the share of production labor in total employment, a decrease which accelerated during the 1980s. Between 1979 and 1989 the employment of production workers in U.S. manufacturing dropped by a dramatic 15 percent from 14.5 to 12.3 million, while non-production employment rose 3 percent from 6.5 to 6.7 million. Trends in Printing, Chemicals and many of the durable goods manufacturing industries were even more dramatic.[1]

There are a number of possible explanations for the skill upgrading that occurred in manufacturing during the 1980s. Perhaps the most plausible explanations are increased international competition and production labor saving technological change, both of which could be expected to decrease the demand of production labor (in the U.S.) Not necessarily independent of these forces, both the severe recession of the early 1980s and the defense build up could have possibly contributed to the shifts.

In this paper we use the ASM data to evaluate the importance of increased international competition, the defense buildup and technological change as possible explanations for the shift in labor demand towards skilled labor. We find that less than 1/3 of the shift away from production towards non-production workers can be accounted for by shifts in product demand away from those manufacturing industries with high shares of production workers in their work force. We attribute much of this "between industry" shift to increased defense procurements and to increased trade during the 1980s. Most of the shift from production to non-production employment occurred within (as opposed to between) four-digit manufacturing industries. These within industry shifts are largely unrelated to imports or defense procurements. In our accounting framework, we attribute the residual to production labor saving technological change. We find skill upgrading to be positively related to investments in computers and computer-related technology as well as to R&D expenditures. These results are consistent with BLS case studies which report that new technologies have generally displaced production workers. We infer

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[1] The BLS Establishment Survey shows very similar trends. The BLS data show that between 1979 and 1989 the employment of production workers in U.S. manufacturing dropped 12 percent from 15,068 to 13,269 thousand while non-production employment rose 3 percent from 5,972 to 6,173 thousand. In durable goods employment of production workers dropped 17 percent, while non-production employment rose 4 percent.

a predominant role for production labor saving technological change in explaining the shift of demand towards skilled labor in the 1980s.

The remainder of the paper is organized as follows. Section I uses the ASM to document trends in the composition of manufacturing employment and discusses the possible explanations listed above. Section II presents accounting exercises that gauge the potential importance of trade and defense in explaining these trends. Section III develops a cost function framework for analyzing cross sectional differences in changes in the utilization of production and non-production workers. Section IV relates the regression results to more qualitative evidence that exists on technological change within manufacturing industries. Section V concludes.

I. Trends within Manufacturing

A. ASM Data

Much of the work in this paper is based on data drawn from the Annual Survey of Manufacturing. The ASM is a survey of manufacturing establishments sampled from those responding to the comprehensive Census of Manufacturing.[2] The ASM collects data on total employment, total payroll, production worker employment, production worker hours, the value of shipments and expenditures on new capital investment, energy and materials. The information is reported for four-digit SIC industries. Information from the ASM was combined with price deflators to construct measures of the capital stock.[3]

Employment is classified in two broad occupational categories, production and non-production workers. These categories are roughly equivalent to blue and white collar occupations. Production workers are defined as "workers (up through the working foreman level) engaged in fabricating, processing, assembling, inspecting and other manufacturing." Non-production workers are defined as "personnel, in-

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2 The sampling frame implies both that the data for census years tend to be more representative and more reliable than the data for non-census years and that there are potential jumps in data series both at the census year and two years later when the new sampling frame is phased in.

3 The original version of these data, covering the 1958–1976 time period, was developed as a joint project by the University of Pennsylvania, the Bureau of the Census, and SRI, Inc. These data were then updated and classified consistently by Wayne B. Gray at the NBER. Gray [1989, 1992] includes a more detailed description of the data.

cluding those engaged in supervision (above the working foreman level), installation and servicing of own product, sales, delivery, professional, technological, administrative, etc." [Bureau of the Census (1986), p. D–16.] These categories apply only to operating plants. Roughly 7 percent of manufacturing employment is in non-operating plants (central offices and other auxiliary establishments). All of the employment in non-operating plants, offices and auxiliary establishments is classified as non-production. Information on these plants is available at only the two-digit SIC level, so we use it in some of our descriptive analyses but not in the more detailed tabulations.

B. The Move Towards Non-production Labor

Figure 1 plots non-production employment as a fraction of total employment. The top line represents the ratio of total non-production employment in manufacturing to total employment, while the bottom line represents the ratio of non-production employment in operating establishments to total employment. There are three striking features to this graph: First, as is well known, production employment is more cyclically sensitive than non-production employment. As a result the fraction of employment that is non-production is countercyclical. Second, peak to peak, the ratio shows a clear upward trend. This trend occurs both for employment in auxiliary establishments and for non-production employment in operating establishments. Third, this trend shows some sign of acceleration in the 1980s: between business cycle peaks years 1959 and 1973, the ratio of non-production workers in operating establishments to total employment rose from 0.227 to 0.234 or 0.05 percentage points per year, between 1973 and 1979 the ratio rose from 0.234 to 0.248 or 0.23 percentage points per year, and from 1979 to 1989 it rose from 0.248 to 0.286 or 0.38 percentage points per year.[4]

There are two reasons why this acceleration in the fraction of employment accounted for by non-production labor can be expected to under-represent the shift

[4] Non-production employment in non-operating establishments was also rising over this period of time: between 1959 and 1973 it rose as a fraction of total employment from 0.036 to 0.049, or 0.09 percentage points per year; between 1973 and 1979 it rose from 0.049 to 0.061 or 0.20 percentage points per year; and between 1979 and 1989 it rose from 0.061 to 0.065 or 0.04 percentage points per year. Note that while within operating establishments the move away from production and towards non-production labor accelerated during the 1980s, in central offices it actually slowed down.

in demand towards skilled labor that occurred during the 1980s. First, the increase in the relative wages of non-production workers that occurred during the 1980s will tend to induce substitution away from non-production labor. Second, to the extent that skill upgrading occurs among either production or non-production workers, the changes in the fraction non-production will underestimate this shift towards more skilled labor. An alternative measure of the changes in the demand for skilled labor is the change in non-production labor's share in the wagebill. Changes in the wagebill share will reflect changes in relative skill levels. The direction of the substitution bias will depend on whether the elasticity of substitution is above or below one. An elasticity below one implies that the change in the wage bill share overstates changes in the (wages constant) relative demand for non-production, labor while an elasticity above one implies the opposite. Figure 2 replicates Figure 1, using the fraction of the wagebill going to non-production labor rather than the fraction of employment. Figure 2 shows a very similar pattern to that in Figure 1: a trend increase in the non-production share of wagebill with a sharp acceleration in the 1980s.

C. The Move Towards Non-production Labor as Skill Upgrading

Since the ASM's only measure of skill is the distinction between production and non-production labor, it is necessary to determine how this classification maps onto the educational and occupational categories available in the CPS. Both conceptually and empirically, the production/non-production worker distinction closely mirrors the distinction between blue and white collar occupations. Tables 1 and 2 compare CPS and ASM data for the years 1973, 1979 and 1987. The fraction white collar corresponds closely with the fraction non-production, with the discrepancy never being larger than 2 percentage points. Using the CPS data we have further broken down white and blue collar employment into broad occupational categories using work done at the Census [U.S. Bureau of the Census, 1989a] to construct consistent occupational groupings. The data also show occupational upgrading occurring within both white and blue collar employment. Between 1973 and 1987, the fraction of white collar workers in clerical jobs drops 18 percent, while the fraction in managerial or professional jobs rises 11 percent. Similarly the fraction of blue collar workers working as operatives drops over 5 percent while the fraction working in the more skilled crafts jobs rises over 20 percent.

In order to relate our work on ASM occupational groups to the literature on the college/high school wage gap, note that the relationship between education and occupation is quite tight. Table 3 shows the distribution of educational attainment by broad occupational groups. As of 1987, the CPS shows 77.6 percent of professional and managerial workers and 69.6 percent of sales workers having at least some college education. On the other hand, only 35.3 percent of clerical workers and 16.8 percent of blue collar workers had some college. At the other end of the scale, 30 percent of blue collar workers had less than a high school education, while this was true for less than 5 percent of white collar workers. While educational attainment was rising within each of the broad occupational categories listed in Table 3, changes across the four broad categories listed in the table account for roughly one-third of the increase in the fraction of the work force that is college educated with the bulk of this being accounted for by shifts between the blue-collar and the white-collar occupations.

As an alternative to working with categories, we constructed skill indexes based on the occupational and educational distribution of the work force within manufacturing. In particular, we calculated mean log hourly earnings for each of the broad occupations identified in Table 1. We then used these means to calculate predicted wages for white and blue collar workers using the occupational distributions in 1973, 1979 and 1987. We did comparable calculations using single years of education in place of occupation. The 1973–1979 and 1973–1987 changes in these indexes are reported in Table 4.

Using a wage metric we find that more than 50 percent of occupational upgrading and more than 25 percent of educational upgrading can be accounted for by the compositional shift of employment away from blue collar labor. We conclude that an important component, though by no means all, of the skill upgrading that occurred within manufacturing during the 1980s can be accounted for by the shift away from blue/collar or production labor. What is more, this wage metric shows skill upgrading to be more dramatic for the white collar than for the blue collar workers. Our wagebill measure will reflect this relative shift.

D. Possible Explanations for the Move Away from Production Labor

What can explain the shift away from production labor in the 1980s? Given the increased relative costs of skilled labor during the 1980s, substitution effects should have worked in the opposite direction. Figure 3 compares employment trends to trends in output, capital and materials. The graph shows capital, materials and output growing at roughly similar rates with employment, especially production worker employment, growing much more slowly. Since, as Figure 3 shows, aggregate capital intensity as measured by the capital/output ratio did not rise appreciably during this period it seems unlikely that capital skill complementarity [Griliches 1969, 1970] can explain the observed shifts in labor demand. On the other hand the figure does show inputs (primarily labor) growing less rapidly than output, suggesting labor-saving technological change.[5]

Other technology indicators are also consistent with an accelerating pace of technological change during the 1980s. Table 5 shows a number of such indicators for various years. NSF data show that R&D expenditures were rising over the 1980s. BEA data show expenditures on computers and communication equipment increasing rapidly since the late 1970s.[6] In addition, a 1988 Census Bureau survey (discussed further in section IV) shows a large fraction of manufacturing establishments using a variety of innovative computer-aided technologies. What is more, BLS industry case studies suggest that the new technologies introduced during the 1970s and 1980s have often involved the loss of semiskilled jobs [Mark, 1987]. Many of these developments are associated with the growing adoption of computer technology within manufacturing.

However, other changes occurred during the 1980s that may have shifted the relative demand for skilled labor within manufacturing. U.S. manufacturing faced increasing international competition. Table 5 shows the dramatic opening of the U.S. economy over the last 20 years. Since within manufacturing the U.S. has typically imported goods that are intensive in less-skilled (production) labor (e.g., apparel) and exported goods that are intensive in skilled (non-production) labor

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[5] The implication of Figure 3 is that Total Factor Productivity was growing over the 1959-1989 period. Since the ASM does not contain information on total compensation, it is not possible to use this data source to compute accurate TFP measures. However, BLS data show multifactor productivity [Gullickson and Harper, 1987] within manufacturing rising at an annual rate of 1.3 percent between 1959 and 1988 and at a rate of 1.6 percent per year between 1979 and 1988.

[6] For a description of how these data were constructed see Gorman et al. (1985) and Musgrave (1986).

(e.g., aircraft), trade will tend to decrease the demand for production labor and increase the demand for non-production labor. Moreover U.S. companies are carrying out an increasing amount of production abroad. Even within specific industries this "foreign outsourcing" is likely to have disproportionate effects on less skilled labor for two reasons. First, production rather than marketing, sales, or product development can be moved abroad. Second, we might expect the more production labor-intensive operations to be moved abroad in order to take advantage of low foreign wages for less skilled workers.

The recession in the early 1980s, the most severe since that of the 1930s, was another change that may have shifted demand towards skilled labor. Manufacturing output remained below trend for the rest of the decade, perhaps partly as a result of the trade deficit. Weak demand for output could be expected to have a disproportionate effect on production labor for two reasons. First, to the extent that the downturn was expected to be temporary, we might expect differential "labor hoarding". Second, in industries facing secular downturns in demand, we expect to observe increases in capital intensity if adjustment costs for capital exceed those for labor. Moreover, in such industries, it is likely to be the older, more labor intensive plants that are closed first if they are undergoing labor saving technological change.

Defense Department procurements also rose dramatically during the 1980s. NIPA data (Table 5) show purchases rising from 2.0 percent of total shipments in manufacturing in 1979 to 4.2 percent of total shipments in 1987. Many defense related-industries tend to employ a disproportionate share of non-production workers. Thus, increases in defense department procurements are likely to have shifted employment within manufacturing away from production workers. This may have been particularly true during the 1980s, given the emphasis put on "high tech" weapons.

It seems clear that aggregate time series data will not allow us to sort out various possible explanations for observed employment trends within manufacturing. In what follows we exploit disaggregated data at the four-digit industry level in two ways. In the following section we decompose shifts in the non-production share of employment and the wagebill into within- and between-industry shifts in order to examine the importance of demand shift explanations. Then, in section

III, we examine the causes of changes in the non-production shares within four digit industries by applying regression analysis to cross- sectional variation in changes in these shares.

II. Industry-Sector Decomposition

A. Within/Between Decompositions

We would expect that some of the forces mentioned above (e.g., the military build-up or international trade) would work by shifting the derived demand for labor across industries, while others (e.g., biased technological change) would shift the skill composition of labor demand within each industry. It is thus useful to decompose the change in the non-production fraction of total employment and the wagebill into shifts that occur within and those that occur between narrowly defined industries. We focus on workers employed in operating establishments because the detailed industry information is only available for them. Since our interest, ultimately, is in understanding the way goods are produced, this is not a serious limitation.

A standard way of decomposing a change in an aggregate proportion into a term reflecting reallocation of employment between industries and another reflecting changes of proportions within industries is as follows:

$$\Delta P_n = \Sigma_i \; \Delta S_i \overline{P}_{n_i} + \Sigma_i \; \Delta P_{n_i} \overline{S}_i \tag{1}$$

for $i = 1 \ldots N$ industries. $P_{n_i} = \frac{E_{n_i}}{E_i}$, is the proportion of non-production labor in industry i. $S_i = \frac{E_i}{E}$, is the share of employment in industry i. The first term on the right reports the change in the aggregate proportion of non-production workers attributable to shifts in employment shares *between* industries with different proportions of non-production workers. The second term reports the change in the aggregate proportion attributable to changes in the proportion of non-production workers *within* each industry. A bar over a term denotes a mean over time. A similar calculation is possible using non-production workers' share in the wagebill rather than employment. [7]

[7] Such a decomposition "weights" workers by their wages, giving more weight to the industries that pay well. This procedure is in spirit similar to working in efficiency units, as has

These "between" and "within" terms are reported in Table 6. Here and for the remainder of the paper, we focus on changes between business cycle peak years, 1959–1973, 1973–1979 and 1979–1987.[8]. Rates are annualized to make changes comparable across time periods. Table 6 shows that both in terms of employment and in terms of the wagebill, the move towards non-production labor *accelerated* over time. Looking first at employment, we see that the shift away from production workers rose from a rate of .069 percentage points per year in 1959–73 to .299 in 1973–79 to .552 in 1979–87, as observed in Figure 1. While the acceleration is evident in both between-industry and within-industry components, the within-industry component dominates the between in each period. This finding is consistent with biased technological change playing a dominant role in explaining the move away from production labor but not factors that shift product demand such as trade or the defense buildup playing a dominant role.

The same patterns emerge for wagebill shares: a trend increase in non-production labor's share which accelerates in the final period. One difference worth noting is that during the 1979–1987 period between-industry shifts play a relatively larger role in the wage-bill decomposition. This is evidence not only that industrial employment was shifting towards non-production labor intensive industries, but also that it was shifting towards industries that use relatively highly paid and presumably highly skilled labor.

Splitting both the 1973–1979 and 1979-1987 periods into subperiods demonstrates that a disproportionate share of both the within- and between-industry shifts occur between the peak and the trough of the business cycle. For example, roughly 70 percent of the within-industry and over 80 percent of the between-industry shifts in both P_n and S_n that occurred between 1979 and 1987 did so between 1979 and 1982. Patterns for the 1973–1979 period were even more striking, with more than 100 percent of the action occurring between 1973 and 1975. Though unrelated to

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been done by others. The one catch is that calculating labor in efficiency units requires weighing by a constant set of wages—something that we have not tried to do. Those working with efficiency units have generally had more complete data on skills (e.g., educational attainment.)

[8] We chose 1987 rather than 1989 for a number of reasons. Since 1987 is a census year, the data should be more reliable. Also, the most recent year available for much of the other data we use is 1987

our research on trends in demand for skilled labor, this is an interesting finding: production worker-intensive industries suffer more during downturns, and all industries tend to use downturns to carry out long term adjustments in the skill mix of their work forces.

Using information on imports, exports and defense shipments by industry, it is possible to further decompose both within- and between-industry changes into "sectors," where the "sectors" of interest are imports, exports and defense procurements. Our goal is to estimate the extent to which both demand shifts due to increases in trade and defense procurements can explain the relative increase in the use of non-production workers.

The source of import and export data is the NBER Trade-Immigration-Labor Market data set. It is an extension of the Bureau of Labor Statistics Trade Monitoring System data set for 1972–1981, based on official trade statistics [Abowd (1991)].[9] Export and import data are available for 432 of 450 industries representing 98 percent of manufacturing output. We imputed 0's where import and export values were missing.[10] Shipments to the Department of Defense are taken from the Bureau of the Census publication, The Survey of Manufacturers' Shipments to the Federal Government. This is a sample of manufacturing plants conducted occasionally in the ASM framework. Sampling is conducted in approximately 70 four-digit industries engaged heavily in contracting for the Federal Government [U.S. Bureau of the Census (1981, 1991).] The Census estimates that the surveyed industries account for the vast bulk of total shipments to the government.[11]

Employment in industry i can be allocated into three final use components:

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9 1984 is the last year for which the NBER trade data exist. Changes in the classification of imports after this date have made it hard to update this data any further. In our tabulations, we extrapolated the data through 1987. In particular, we estimated 1987 imports as a fraction of shipments in an industry as $8/5 \times (i/y_{1984} - i/y_{1979}) + i/y_{1979}$. Similar extrapolations were done for exports. To check that our results for the decompositions were not unduly influenced by these imputations, we redid the calculations for the 1979–1984 period and obtained results very similar to those reported in Table 7.

10 We experimented with eliminating the 18 industries with missing data on imports and exports. Doing so made no qualitative differences to our conclusion.

11 One problem with these data is that subcontracts to the department of defense, representing roughly one third of all procurements, are not separately identified. As a result, such subcontracts are double counted, resulting in an overestimate of total defense procurements by about 30 percent.

exports, defense, and domestic civilian production.

$$E_i = E_i^X + E_i^D + E_i^{DC} \tag{2}$$

The employment attributable to domestic civilian consumption (as opposed to production) in the home economy can be written as the sum of domestic civilian production and import components

$$E_i^C = E_i^{DC} + E_i^M \tag{3}$$

where the final term represents the employment that would be required to produce imported goods domestically. (The term, E_i^C, is analogous to "C" in the national accounts. It includes employment displaced by imports consumed domestically.) Substitution yields

$$E_i = E_i^X - E_i^M + E_i^D + E_i^C \tag{4}$$

That is, employment is attributed to exports, defense and domestic civilian consumption, less that portion of employment due to domestic civilian consumption which is employed abroad producing imports. Assuming that employment and non-production employment in each sector of an industry are allocated in the same proportions as output in the sector, we use industry-specific data on shipments of import, export and defense goods to estimate each of the components of equation (4). Specifically, we estimate E_i^X as $E_i \times (exports_i/output_i)$, E_i^M as $E_i \times (imports_i/output_i)$ and E_i^D as $E_i \times (defense\ output_i/output_i)$.[12] E_i^C is defined as the residual. Similarly, the sum of non-production workers in industry i can be divided into sectors as

$$E_{n_i} = E_{n_i}^X - E_{n_i}^M + E_{n_i}^D + E_{n_i}^C \tag{5}$$

Employment shares for each industry in total employment can be expressed as

[12] Data on employment in defense production is actually available in slightly more detail. It allows $E_i^D = \Sigma_k E_{i_k}$ (defense shipments$_{i_k}$/output$_{i_k}$) where k indexes plants in industry i.

$$S_i = S_i^X + S_i^M + S_i^D + S_i^C \tag{6}$$

where $S_i^J = E_i^J/E$ for $J = (X, D, C)$, $S_i^M = -E_i^M/E$ is defined as negative and E represents total employment in manufacturing (i.e., $E = \Sigma_i E_i$).

We can further decompose the between term in equation (1) into sectors by substituting (6) into (1).

$$\begin{aligned}\Sigma_i \Delta S_i \overline{P}_{n_i} =& \Sigma_i \Delta S_i^X \overline{P}_{n_i} + \Sigma_i \Delta S_i^M \overline{P}_{n_i} + \Sigma_i \Delta S_i^D \overline{P}_{n_i} + \Sigma_i \Delta S_i^C \overline{P}_{n_i} \\ =& \Sigma_i \Delta S_i^X (\overline{P}_{n_i} - \overline{P}_n^C) + \Sigma_i \Delta S_i^M (\overline{P}_{n_i} - \overline{P}_n^C) + \Sigma_i \Delta S_i^D (\overline{P}_{n_i} - \overline{P}_n^C) \\ &+ \Sigma_i \Delta S_i^C (\overline{P}_{n_i} - \overline{P}_n^C)\end{aligned} \tag{7}$$

In this accounting exercise we measure reallocations to each sector of each industry relative to a residual pool of labor in sector C with proportion of non-production workers $\overline{P}_n^C$ ($\overline{P}_n^C = \frac{\Sigma_i S_i^C \overline{P}_{n_i}}{\Sigma_i S_i^C}$). Equation (7) approximates a more accurate decomposition that would be possible if $P_{n_i}^J$ rather than P_{n_i} were available for each industry-sector term.[13]

Within industry changes in the aggregate P_n can also be decomposed into sectors.

$$\begin{aligned}\Sigma_i \Delta P_{n_i} \overline{S}_i =& \Sigma_i \Delta P_{n_i} \overline{S}_i^X + \Sigma_i \Delta P_{n_i} \overline{S}_i^M + \Sigma_i \Delta P_{n_i} \overline{S}_i^D + \Sigma_i \Delta P_{n_i} \overline{S}_i^C \\ =& \Sigma_i (\Delta P_{n_i} - \Delta P_n^C) \overline{S}_i^X + \Sigma_i (\Delta P_{n_i} - \Delta P_n^C) \overline{S}_i^M + \Sigma_i (\Delta P_{n_i} - \Delta P_n^C) \overline{S}_i^D \\ &+ \Sigma_i (\Delta P_{n_i} - \Delta P_n^C) \overline{S}_i^C + \Delta P_n^C\end{aligned} \tag{8}$$

[13] Our calculations ignore the indirect effects of trade on the composition of employment. Given that much of industrial production serves as intermediate inputs for other industries, the effects of "trade" percolate to supplying industries as well. For example, automobile imports lower the demand not just for domestically produced automobiles, but also for domestically produced steel. Our calculation ignores these effects. A procedure that uses the I-O tables to "pass" some of these effects through might be appropriate, but it cannot be done at the 4-digit level. Studies that have looked at these indirect effects have usually found them important though not as important as the direct effects, though such studies have focused on total employment rather than the composition of employment [Dickens, 1988].

Equation (9) is designed to measure contributions of each sector to the overall within-industry increase in ΔP_n. Each industry-sector term $(\Delta P_{n_i} - \Delta P_n^C)\ \overline{S}_i^J$ in this decomposition expresses the contribution of ΔP_n in sector J of industry i to the general increase in the aggregate P_n. Industry-sectors with faster than average skill upgrading have positive contributions, while those with slower than average upgrading have negative contributions. The assumption used in this form is that if $\overline{S}_i^J$ had been different, employment would have been allocated to (or from) a use with ΔP_n^C ($\Delta P_n^C = \frac{\Sigma_i \overline{S}_i^C \Delta P_{n_i}}{\Sigma_i \overline{S}_i^C}$), the average for the domestic consumption sector. We sum these terms over all industries for each sector to measure the contribution of a sector to the within-industry variation. The fourth summation in equation (9), $\Sigma_i(\Delta P_{n_i} - \Delta P_n^C)\overline{S}_i^C$, is equal to zero.[14]

It is possible to decompose changes in non-production workers' share in the total wagebill analogously. Regardless of whether we are dealing with changes in non-production workers' share in employment or in the wagebill, we have 450 industries and four sectors, so equations (7) and (8) contain 1,800 terms each, while equation (9) contains 1,801. We confine our interest to the eight sectoral sums, given in Table 7.

Breaking the "between" industry component down by sectors in the 1979–87 period, we see that for employment (column 1) the largest sectoral increase is in defense, which accounts for 0.072 percentage points. Imports and exports together account for 0.048 points, and the domestic consumption sector (the residual) accounts for 0.044 points. Surprisingly, perhaps, the role of trade in shifting employment away from production labor-intensive industries is small.

The wagebill decompositions show similar patterns, though here the tabulations show imports actually lowering the non-production workers' share during the 1979–1987 period. The opposite signs of the effect of increased imports on employment and wagebill proportions of non-production labor can be explained as follows: During the 1980s imports were displacing workers in both "low tech" (e.g., apparel) and "high tech" (e.g., electronics) industries. The displacement of workers

[14] Again, it is worth noting that Both (8) and (9) only approximate a more accurate decomposition that would be possible if $\Delta P_{n_i}^J$ rather than ΔP_{n_i} were available for each industry-sector term.

in "low tech" industries works to raise the non-production share of the remaining work force, while the displacement of workers in "high tech" industries has the reverse effect. The employment decompositions put relatively more weight on the former industries, while the wagebill decompositions put relatively more weight on the latter.

Turning to the "within" industry component of ΔP_n in the 1979–87 period, the second column indicates the contributions of each sector to within-industry skill upgrading. The small positive term for defense indicates that skill upgrading occurred slightly faster in industries with large defense sectors than in the domestic consumption sector. The same is true for export and import sectors (Recall that S^M is defined as negative. Thus negative import terms imply that skill upgrading was occurring more rapidly within importing industries.). The main conclusion from this sectoral analysis is that the skill upgrading within the domestic consumption sector accounted for almost all of within-industry skill upgrading and indeed for most of the skill upgrading overall. This conclusion holds for the earlier periods as well. Most of the change and most of the acceleration in both P_n and S_n is due to within industry skill upgrading unrelated to either trade or defense.

Individual industry – sector components of the between terms reported on in Table 7 illustrate the concentration of skill upgrading in the defense sector. In Table 8 we report individual components that contributed over 0.005 points to the 1979–1987 between component of the change in the wagebill share.[15] Examining the individual industry components of the defense sector, we find that two industries alone account for two-thirds of the 0.101 point annual increase attributed to defense between in Table 7. These are telecommunications, radio and television (SIC 3662) and guided missiles and space vehicles (SIC 3761). These industries employ a disproportionate share of non-production workers and, over the 1980s, shipped a large and growing share of output to the department of defense. Turning to the most influential of the import industry terms, a reduction of 0.036 points in S_n between 1979 and 1987 can be attributed to increased imports of computers (SIC 3573-3574) and semiconductors (SIC 3674). Both have high and increasing import/output

[15] A table showing industries that contributed large shares to the 1979–1987 change in P_n contains essentially the same list of industries.

ratios and high proportions of non-production workers. More conventional imports are canned fruit and vegetables (SIC 2033), footwear (SIC 3149), and motor vehicles and passenger car bodies (SIC 3711), each with low proportions of non-production employment and large increases in imports.

Table 9 lists the 17 industries explaining the largest fraction of the within-industry change in S_n.[16] This table reports on where skill upgrading took place. The industries listed account for more than 25 percent of the aggregate change in S_n. While some of the industries represented are large importers (e.g., semi-conductors, SIC 3674), others are not (e.g., newspapers, SIC 2711; aircraft, SIC 372; telecommunications, SIC 366). The literature on the semi-conductor industries emphasizes outsourcing as well as technological change as important in explaining the loss of production jobs. What is striking is how many of the industries listed in Table 9 are known to have introduced major innovations over the last decade or so. For example, the literature on the printing and aircraft industries emphasizes process innovations, and the literature on the electronics industry emphasizes both process and product innovations. The BLS case studies [U.S. Department of Labor, 1982a, 1982b, 1986] which mention these industries include extensive discussions of production labor-saving innovations affecting these industries.

C. The Impact of Trade and the Defense Buildup

What does all of this imply about the impact of changes in trade and the defense buildup on skill upgrading within manufacturing industries? It is useful to think about effects that work across industries versus those that might work within-industries. Within manufacturing, defense procurements and exports tend to be concentrated in industries that are intensive in non-production labor (e.g., aircraft), while imports have typically been concentrated in industries that are intensive in production labor (e.g., apparel). Thus we should expect that changes in the amount or kinds of goods we import or export or changes in the value of defense department procurements would tend to shift production across industries and as a result would change the composition of employment. The between-industry components in Table 7 are meant to pick up these effects. Implicitly we are assuming that imports, exports and shipments to the defense department do not affect domestic demand so

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[16] A comparable table for employment shows a very similar list of industries.

that a dollars' worth of imports displaces exactly a dollars' worth of domestically produced goods.[17]

It also seems possible that either the defense buildup or trade could be partly responsible for the within-industry shifts that we observe. To the extent that, within an industry, defense department production tends to be non-production labor intensive (as would be the case if the production of fighter aircraft required relatively more technicians than the production of passenger planes), increases in defense department procurements as a fraction of total industry output would work to raise the non-production employment share. Similar effects could be true for either imports or exports. While we believe that these effects may be important for some industries, a number of considerations lead us to suspect that it cannot account for the bulk of the observed, within-industry, skill upgrading. First, Table 7 shows that while skill upgrading was occurring a bit more rapidly both in defense intensive and import intensive industries than it was in the residual sector, these effects are small. Furthermore, changes in defense's share in industry employment and the import to domestic production ratio's are only mildly correlated with changes in the non-production workers' share of employment or the wagebill. The correlation between changes in the defense share of employment and changes in the non-production workers' share in employment and the wagebill are 0.17 and 0.09 respectively. While these correlations are not trivial in magnitude, they imply that the defense buildup can account for only 7.7 percent of the shift in the employment share and 4.5 percent of the shift in the wagebill share.[18] The correlation between changes in the import to shipment ratio and changes in the non-production share in either employment

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17 These assumptions seem reasonable when considering exports and shipments to the defense department, but could easily be questioned when considering imports. One way to check the assumption is to compare the effect of trade on employment obtained using our accounting methods to that obtained using model-based approaches. Revenga [1992] estimates that between 1980 and 1985 imports reduced employment by between 4.5 and 7.5 percent in 38 trade-sensitive industries. Using the numbers reported by Revenga, but accounting methods, we estimate that imports reduced employment by 5.9 percent – a number in the middle of the range of Revenga's preferred estimates. Thus, at least in this instance, model-based and accounting-based estimates seem to lead to quite similar conclusions.

18 These fractions are calculated by regressing the change in non-production workers' share of employment or the wagebill on the change in the share of employment working on defense contracts. The share of upgrading accounted for is then the regression coefficient times the mean of the explanatory variable over the mean of the dependent variable. Equivalently, one can write the share as $\rho_{yx} \times (S_y/S_x) \times (\overline{x}/\overline{y})$.

or the wagebill are also quite small – 0.19 and 0.01, respectively. These numbers imply that imports can account for 5 percent of the shift in the employment share and less than one percent of the shift in the wagebill share.

One needs to be a bit careful in interpreting the small import share correlations. The fact that the correlations are close to zero shows that skill upgrading is occurring no more rapidly in import intensive industries than in other industries. However, suppose that the industries that manage to lower costs through production labor saving technological change are the ones that manage to stave off imports. In this case, one might find less skill upgrading in industries that showed large increases in imports than in industries that did not. However, it would be wrong to infer that imports contributed negligibly to skill upgrading. What this story implies is that import substitution is not the only factor accounting for the within industry shifts.

A simple calculation suggests that imports can not be responsible for the bulk of the changes we observe. Assuming that imports displace production but not non-production labor and that imports embody the same amount of production labor as do domestically produced goods in the same industry, but no non-production labor, we can calculate for each industry the number of production workers displaced by the growth of imports between 1979 and 1987 as $\Delta(imports/total\ shipments) \times$ *production employment*. These calculations suggest that had imports been at their 1979 level in 1987, the employment of production workers would have been 4 percent higher, and translates into a 0.57 percentage point increase in their share in total employment. Since the production workers share had dropped 3.10 percentage points between 1979 and 1987, this calculation attributes 18 percent of the total within industry decline directly to increased imports [19] Assuming that imports embody twice as much production labor but the same amount of non-production labor as domestically produced goods in the same industry gives similar results of somewhat smaller magnitude.

The calculations above should be seen as crude upper bounds on the within-industry affect of imports. In most cases, the assumption that the labor embodied in imports is similar in magnitude and composition to the labor embodied in domestically produced goods in the same industry seems quite natural. Thus, for

[19] A similar calculation using wage bill rather than employment shares gives very similar results.

example, were imported automobiles or TVs made in the U.S. they would require roughly the same amount labor as do the automobiles and TVs currently produced in the U.S.

There is one instance in which it may be natural to assume the imports into an industry are more labor intensive than domestically produced goods in the same industry. To the extent that domestic firms outsource production overseas, it is likely that the outsourced parts are unskilled labor intensive. Again, some simple calculations are possible which suggest that outsourcing cannot be responsible for the bulk of the changes we observe. The 1987 Census of Manufacturing included a direct question regarding the purchase by establishments of foreign materials. These data show that in 1987 the total cost of material purchased by establishments from foreign sources was 104 billion dollars, or 8 percent of all materials purchased and 30 percent of all imported manufactured goods. Foreign materials purchased include substitutes for domestically produced materials as well as substitutes for products that would have been produced within the purchasing establishment's own industry. While we know of no reliable way to distinguish uses for the material purchased from foreign sources, we note that census data show that only a small fraction (< 10 percent) of purchased materials come from an establishment's own industry.[20] This fact suggests that only a small fraction of foreign materials purchased represent outsourcing (as they do not replace domestic production in the same industry).

As before, in our calculation we assume that imported materials displace production but not non-production labor. In particular we assume that imported materials embody the same amount of production labor as do domestically produced goods in the same industry, but no non-production labor. Thus, for each industry, we calculate that the number of production workers displaced by outsourcing as of 1987 as (*imported materials/total shipments*) $\times$ *production employment*. These calculations suggest that the employment of production workers would have been 2.8 percent higher in 1987 had there been no outsourcing. This translates into a 0.76 percentage point increase in production workers' share in total employment. Within industry, production workers' share had dropped 4.22 percentage points be-

[20] Data drawn from the materials files of the 1987 Census of manufacturing shows that 2 percent of materials purchased originate in the same four-digit industry as purchased the material. 7 percent originate in the same three-digit industry.

tween 1973 and 1987. Thus, this calculation would suggest that outsourcing could directly account for 16 percent of the decline in the production worker share of employment that occurred over this time period.[21]

While we expect that only a fraction of the materials that an establishment purchases from foreign sources will represent outsourcing, the Census category misses one dimension of outsourcing. The census instructions state that "items partially fabricated abroad which reenter the country" should not be included as "foreign materials." Such items would normally enter the country under items 806 and 807, schedule 8 of the Tariff Schedule of the United States. In 1987 the value of such items totaled a not insignificant 68.6 billion dollars. However, the automobile industry that accounted for only 3 percent of total skill upgrading accounted for roughly two-thirds of such imports. Eliminating both the auto industry and domestic content of such items reduces the 68.6 billion to 14.0 billion or roughly 0.5 percent of the value of manufacturing shipments that year—too small a quantity to matter very much [U.S. International Trade Commission, 1988].

Outsourcing may be important in some industries. For example, as of 1987, 806 and 807 imports represented 57 percent of imports in the auto industry and 44 percent of imports of semiconductors. A calculation similar to the one done above suggests that these imports are sufficient to account for more than 100 percent of the shift away from production workers that occurred in the auto industry and one-third of the shift that occurred in semiconductors.[22] However, the point is that foreign outsourcing is concentrated enough in specific industries that it is hard to imagine that it can account for anything more than a small fraction of the total, within-industry shift away from production labor.

These estimates are clearly crude. On the one hand, not all foreign materials represent outsourcing. On the other, it is not at all clear either that no nonproduction labor is embodied in imported materials or that the production labor implicitly embodied in foreign imports is similar in magnitude to the labor embodied in domestically produced goods in the same industry. Still, these calculations would

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21 A similar calculation using wagebill rather than employment shares gives very similar results.

22 Figures on the overseas production of semiconductors [U.S. International Trade Commission, 1982] are in line with these calculations

seem to suggest that while outsourcing might be important for some industries it cannot account for the bulk of the skill upgrading that has occurred within manufacturing over the last two decades.

III. Cross Sectional Comparisons

A. A Cost Function Framework

To further explore factors that might explain within-industry changes in non-production labor's share in employment or the wagebill it is natural to turn to a regression format. It is possible to put much of what we do into a cost function framework. We begin by assuming that over the time horizons we are working with (i.e. 6 or more years) capital can treated as a fixed factor but that both production and non-production labor should be treated as variable. Assuming that the variable cost function has a translog form we can write it as

$$\begin{aligned} ln(CV) = &\alpha_0 + \alpha_y ln(Y) + \Sigma_i \alpha_i ln(W_i) + \beta ln(K) + \\ &.5\gamma_{YY} ln(Y)^2 + .5\Sigma_i \Sigma_j \gamma_{ij} ln(W_i) ln(W_j) + .5\delta ln(K)^2 \\ &\Sigma_i \rho_{Y_i} ln(Y) ln(W_i) + \Sigma_i \rho_i ln(W_i) ln(K) \\ &\pi ln(Y) ln(K) + \phi_t t + .5\phi_{tt} t^2 \\ &\phi_{tY} t ln(Y) + \Sigma_i \phi_{tW_i} t ln(W_i) + \phi_{tK} t ln(K) \end{aligned} \tag{10}$$

Where CV represents variable costs, Y is value added, the $W's$ represent unit costs of the variable factors and K represents capital. The coefficients on t represent technological change.

Cost minimization implies share equations of the form

$$S_i = \alpha_i + \rho_{Y_i} ln(Y) + \Sigma_j \gamma_{ij} ln(W_j) + \rho_i ln(K) + \phi_{tW_i} t \tag{11}$$

Differencing yields

$$dS_i = \phi_{tW_i} dt + \rho_{Y_i} dln(Y) + \Sigma_j \gamma_{ij} dln(W_j) + \rho_i dln(K) \tag{12}$$

Homogeneity of degree one in prices implies

$$\Sigma_i \gamma_{ij} = \Sigma_j \gamma_{ij} = \Sigma_i \rho_i = \Sigma_i \phi_{tW_t} = 0 \tag{13}$$

With two variable factors this gives equations of the form

$$dS_i = \phi_i dt + \gamma dln(W_i/W_j) + \rho_i dln(K) + \rho_{Y_i} dln(Y) \tag{14}$$

Constant returns to scale implies $\rho_{Y_i} = -\rho_i$. Imposing this restriction, and assuming that neither γ nor ρ vary across industries gives estimating equations of the form:

$$dS_{np_j} = \beta_0 + \beta_1 dln(W_{np_j}/W_{p_j}) + \beta_2 dln(K_j/Y_j) + \epsilon_j \tag{15}$$

where np and p indicate non-production and production labor respectively and j indexes industry. β_1 will be positive or negative according to whether the elasticity of substitution between production and non-production labor is below or above 1. Capital-skill complimentarily implies that $\beta_2 > 0$, β_0 is a measure of the cross-industry average bias in technological change while $\beta_0 + \epsilon_j$ represents the industry-specific bias. The equation for dS_{p_j} is redundant.

A few remarks are worth making about the specification before turning to the actual estimates. First, while Y represents value added, in the empirical work we use shipments instead. Our reason for doing so is entirely pragmatic. Good price deflators for materials do not exist at the four-digit level. This makes it impossible to construct reliable real value added measures. As an alternative, we tried explicitly including materials as a third-variable factor. The estimates of the elasticity of substitution between materials and non-production labor was almost exactly the same as the elasticity between materials and production labor. The implication of these estimates is that while changes in the price of materials might cause substitution towards or away from labor, such changes will not affect the relative utilization of production and non-production labor.[23] Second, while it may be plausible to treat capital and output as exogenous, it is not plausible to treat

[23] Distinguishing between energy and non-energy materials produced similar results.

relative wages as exogenous. In fact, it is not at all clear that there is any useful exogenous cross sectional variation in relative wages. While some of the variation that does exist may have to do with the different skill mixes of the labor employed by different industries, some of it probably involves within sector skill upgrading. In other words, price changes are confounded with quality changes. Furthermore, given the definitional relationship between our dependent variable, changes in the non-production workers' share in the wagebill, and our wage measures estimates will suffer from a version of division bias. However on the assumption that, to first approximation, the price of quality adjusted production and non-production labor does not vary across industries $dln(W_{np_j}/W_{p_j})$ will be a constant. Thus ignoring relative wages, as we do, will affect the constant term in our equations but nothing else.

Various features of the ASM introduce noise in the time series behavior of the data. In particular, the fact that the sample is redrawn every five years tends to introduce jumps in the series at five year intervals. There is also a tendency for firms to migrate from one industry to another (see Siegel and Griliches, 1992). Initial inspection of the data indicated that most of the large jumps occur in small industries. A natural way to minimize the impact of these small industries is to weight by some measure of industry size. We chose to weight by the industry's share in total manufacturing payroll averaged over 1959 and 1973 for the 1959–1973 change, 1973 and 1979 for the 1973–1979 change, and over 1979 and 1987 for the 1979–1987 change. Doing so implies that our dependent variable aggregates to the within-industry changes used in the decompositions reported in Tables 6 and 7.[24]

[24] We have experimented with alternative dependent variables—the change in non-production workers' share in total employment and the change in the log of the ratio of non-production to production worker employment. Results using these alternative dependent variables are very similar to those reported here. We have also experimented with a number of alternative samples. We tried eliminating the 57 industries whose fourth digit was a 9. There are a variety of reasons to be more suspicious of the data in these 'nec' industries than in others. These industries are the ones most likely to have firms migrate in and out of them. Also, to the extent that we match data from other sources with this ASM data set, these matches are often not possible for four-digit industries that end in 9. We also tried eliminating the four-digit computer industry (SIC 3573). The computer industry shows growth in output unmatched by any growth in inputs. One plausible explanation for this phenomenon is that input and output deflators have not been correctly matched. In both cases, results for the smaller samples were very similar to the results we report.

Table 10 reports summary statistics for the three subperiods. The means reproduce what we have seen already. The annual growth in the share of wages going to non-production labor rose from 0.07 percentage points per year during the 1960s to 0.21 percentage points per year during the 1970s and to 0.47 percentage points per year during the 1980s. The growth of output dropped from 3.9 percent per year during the 1960s to 1.7 percent per year in the 1980s, while capital accumulation dropped from 4.2 percent per year in the 1960s to 2.8 percent per year in the 1980s. During the 1960s, output grew at almost the same rate as did capital. As a result, capital intensity grew only slowly (0.3 percent per year). In contrast, during the 1980s, capital was growing more than 1 percent per year faster than output. Distinguishing between plant and equipment, we see that for each of the three time periods, equipment grew more rapidly than plant. In fact, plant grew more slowly than output, implying that plant intensity (i.e., plant/output) dropped over the period.

Table 11 shows the share equation (15) estimated for the 1979–1987 period. The first specification includes $d\ ln(K/Y)$, while the second includes $d\ ln(E/Y)$ and $d\ ln(P/Y)$ separately. The last two columns repeat the first two but include $d\ ln(Y)$ as an extra covariate. A quick way to see how much of the skill upgrading these variables explain is to compare the constant term in each equation to the mean change in $d\ Sn$ over the period, 0.468. In the first specification, $d\ ln(K/Y)$ picks up a significant positive coefficient consistent with capital skill complementarity, but this effect explains a little less than 10 percent of the change in $d\ S_n$ over the period. When plant and equipment are included as separate variables, it is the equipment variable that picks up a significant positive coefficient. When a separate coefficient on output is allowed it is always positive, but smaller than that on capital or equipment. The implication is that, holding capital intensity (K/Y) fixed, output growth is positively correlated with the growth in non-production labor's share, while holding capital constant (K), output is negatively correlated with the growth in non-production labor's share. There are a number of possible interpretations of these results. In the short run, with the capital stock constant, drops in output could be expected to disproportionately affect production workers. In the long run, holding capital intensity constant, increases in output could reflect technological change. The positive coefficient then might be interpreted as an indication that technological change was production labor saving. Together $d\ ln(K/Y)$ and $d\ ln(Y)$ explain about 25 percent of the increase in demand for skilled labor.

In Table 12 we combine the three periods, including dummy variables for the second and third time period. Thus all identification comes from the cross-sectional variation (of growth rates) in the data. The first of the five specifications includes only the two time period dummies, the second includes $d\ ln(K/Y)$ as well, the third separates $d\ ln(P/Y)$ and $d\ ln(E/Y)$ entered separately, while the 4th and 5th repeat the third and fourth but include output separately. The first column reproduces the now familiar result that the change in wage bill share of non-production labor is higher in the second than in the first period, and even higher in the third (the acceleration). When the plant and equipment intensity variables are included they explain about 10 percent of the accelerated move away from non-production labor, but when $d\ ln(Y)$ is added, the capital and output variables together explain none of the acceleration. While capital intensity was growing more rapidly in the 1980s than it was in the 1960s, output was growing more slowly.

To what extent can we attribute the acceleration of the trend away from production labor to the severity of the 1980s recession? If it was the recession that drove the shift in the composition of labor we might expect that industries that were hit harder by the recession would tend to be the ones that showed the biggest shift away from production labor. In fact the weighted correlation between $d\ S_n$ and $d\ ln(Y)$ is small but positive in each of the three periods ranging from a maximum of 0.06 for the 1973-1979 period to a minimum of 0.02 for the 1979-1987 period.

To summarize, while our evidence does suggest capital-skill complimentarily in general and equipment skill complimentarily in particular, capital accumulation seems capable of explaining only a fraction of observed skill upgrading. Within our framework, shifts away from production and towards non-production labor not explainable by measured factors can be interpreted as representing biased technological change. While this is not the only possible explanation for these results, we have seen that the most plausible alternative explanation – foreign outsourcing – does not seem capable of explain the bulk of the observed change. While our finding that technological change has been production labor-saving is consistent with much of the recent literature on the effect of the computer revolution on production technology, it would be nice to find more direct evidence for this interpretation.

B. Indicators of Technological Change

Perhaps the most natural approach would be to include a measure of the growth in total factor productivity in our regressions. In fact, at the two digit level the industries that show substantial productivity growth also show the most skill upgrading. Yet there are two arguments against including TFP measures in our regressions. Total factor productivity is defined as the growth of output minus the share weighted growth of inputs $d\ TFP = d\ ln(Y) - \Sigma_i S_i X_i$. Thus there is a definitional relationship between our capital intensity variable and $d\ TFP$, so any errors in one are likely to be correlated with the other. Furthermore, it is not really possible to calculate accurate TFP measures from the four-digit ASM data. Recall that the data do not include the central office personnel, nor do the payroll data represent full labor costs. Thus, the labor share we would calculate would substantially underestimate labor's actual share.

As an alternative to TFP we include in our regressions variables that are plausibly correlated with productivity growth: investment in computers and research and development expenditures. In 1977, 1982 and 1987 the census of manufactures included a question on investment in computers. We have included in our regressions several measures based on these data, computer investments in 1977, 1982 and 1987 as a share of total investments in each year and the change in this share between 1977 and 1987. While ideally we would like to have a measure of the change in the total stock of computers, such a measure cannot really be derived from investment data at only three points of time. On the other hand, under the assumption that what varies across industries is the adaptability of different technologies to computerization, the cross sectional variation in the increase in computer investment should proxy for the variation in computer capital stock.

Table 13 reports weighted means and first-order correlations between computer investments variables. The data show investments rising dramatically over this period of time. Not surprisingly, the three computer investment variables are reasonably highly correlated with each other. They are also reasonably highly correlated with the change between 1979 and 1987 in the non-production workers' share in the wage bill, $d\ S_n$, the correlation being higher for the more recent investment measures.[25]

Table 14 shows the result of including each of the computer investment variables, one at a time, in our basic set of regressions. Regardless of specification, these computer investment variables are highly statistically significant. They are also quantitatively large. In 1982 the average share of computers in total investments was 0.039. Using the estimated coefficient from the second column in Table 14, we multiply this .039 by .031 to get 0.0012—26 percent of the average change over the 1979–1987 period in the non-production workers' share in the wagebill. Using the 1987 numbers we get 0.0024, or 52 percent of the average change.[26] In the fourth column of Table 14 we include both 1977 and 1987 variables. In this specification the coefficient on the 1977 variable is small and statistically insignificant while the 1987 variable picks up a coefficient very similar to the one it picked up when it was the only computer investment variable included in the regression. An alternative parameterization includes the 1977 and the 1977–1987 change in the same equation. In this parameterization, both variables pick up significant coefficients—both the level of computer investments towards the end of the 1970s and the acceleration over the next decade seem to matter.[27] *Thus, investments in computers alone would seem to account for between one-quarter and one-half of the within-industry move away from production labor that occurred over the 1980s.*

While these results are striking, their interpretation is not clear cut. The relationship between computer investment and the non-production share could be mechanical rather than causal. Suppose that it is non-production workers who typically use computers. A rise in the non-production workers' share in total employment might then increase the share of computers in total investments in the same way that it would increase the share of desks in total investments. One check on this

25 Not all industries reported computer investments. Of our 450 industries, 169 failed to report any computer investments in 1977, as did 45 in 1982 and 35 in 1987. In the results reported we have treated these missing values as 0's. Correlations based on pairwise complete observations are very similar to those reported.

26 We experimented with including missing data dummies in these regressions. Doing so hardly alters the results. The coefficients on these dummies are uniformly small in magnitude and statistically insignificant. These results are consistent with our presumption that unreported implied small.

27 The coefficients on the two variables were 0.024 (0.008) and 0.031 (0.006) respectively.

possibility is to regress the change in the log of production and non-production employment on the log of capital intensity, the log or output and the share of computers in total investments as of 1987. The coefficient on the computer variable is -0.20 (0.18) in the non-production worker equation and -0.45 (0.17) in the production worker equation. These estimates imply that a one percent increase in the share of computers in total investments lowers production employment by 0.45 percent while lowering non-production employment by 0.2 percent. Thus, computers would seem to be substitutes (not complements) for both production and non-production labor, but with the larger effect on production labor.

We were also worried that what was happening might be that the industries that were innovating and moving away from production labor in the long run also happened to be the industries that invested in computers. As a check on the interpretation of the computer investment variable, we tried including the computer variables in regressions for the earlier time periods. In results not reported we found that even in the earlier periods, computer variables do pick up significant coefficients, though, interestingly enough, the 1977 rather than the 1987 investment variable tends to pick up the largest effect. While it would be possible to interpret the results from the 1973–1979 period as actually having something to do with the computer investments, it is hard to do this for the 1959–1973 period. When both the 1977 level and the 1977–1987 change are included in such regressions, we find that the level variable picks up comparable coefficients in the three periods, but that the coefficients on the change variable are both small and statistically insignificant in the earlier periods. This suggests that the level of computer investment in 1977 may reflect more permanent differences across industries while the industry-specific change in investment reflects technological changes that were occurring in those industries during the 1980s.

We also experimented with another productivity indicator—R&D expenditures by three-digit SIC available in 1974. These data were originally assembled by Scherer and a complete description of them can be found in his 1984 paper. Scherer used data from the Federal Trade Commission's Line of Business Survey to calculate R&D expenditures by industry. These are referred to by him as *R&D by industry of origin*. However, since most innovations are product rather than process innovations, it is not at all clear that productivity increases will accrue primarily to the industries in which the *R&D* is performed. Scherer then used patent data to map the *R&D* expenditures by *industry of origin* into *R&D* expenditures by *industry of use*. We use both constructs, including in our regressions the estimated R&D expenditures as a fraction of 1974 shipments in that industry.[28]

Table 15 reports simple correlations between these *R&D* measures, computers as a share of total investment in 1987 and the change in the non-production workers' share in the wagebill between 1979 and 1987. While the *R&D* expenditures variables are based on a single year of data, as long as the relative rankings of industries did not change much over time, this single year measure can proxy for the permanent differences in the *R&D* intensity of industries. As expected, the correlations between the various technology indicators are all positive, though they are far from one and the correlation between the *R&D* by industry of use and the computer investment variable is remarkably weak. The correlation between each of the technology indicators and $d\ S_n$ are also all positive and reasonably large.

Results from including the *R&D* measures in the share equations are reported in Table 16. Whether we use the data on *industry of origin* or *industry of use*, the R&D variables pick up significant coefficients. They suggest that a one percentage point rise in R&D expenditures increases the annual rate of change in S_n by roughly 0.10 percentage points.[29] Using the average *R&D* intensity reported in Table 15, we calculate that *R&D* expenditures accelerated the shift away from production labor by about 0.10 percentage points per year if we use the industry of origin measure and by about 0.05 percentage points if we use the industry of use measure. Columns (4) and (5) include both the computer and each of the *R&D* measures in the same equations. In each case, both variables pick up significant coefficients and together they account for roughly 50 percent of the move away from production labor.

We tried entering the *R&D* variables into regressions done on the earlier time

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[28] Scherer actually constructed two measures of *R&D* by *industry of use*. To construct the measure we use, Scherer used the patent data to proportionately allocate *R&D* expenditures by industry of origin to industry of use. In the second measure, Scherer tried to capture the public goods nature of inventions. This second measure performed relatively poorly for Scherer and has not been included in the tabulations we report.

[29] From a theoretical point of view, one might expect that *R&D* by *industry of use* should dominate *R&D* by *industry of origin*, however, given the nature of the way the *industry of use* measure was constructed, it seem plausible that this latter variable contains more measurement error.

periods. The relationship between the *R&D* expenditures and $d\ S_n$ tends to be the strongest during the 1979–1987 period and weakest in the 1973–1979 period. While the differences between the estimated coefficients are not significant, the pattern is consistent with the pattern of *R&D* expenditures that occurred over this time period, with these expenditures being higher in the 1960s and 1980s than they were in the 1970s.

The results reported above would seem to support the notion that biased technological change has been an important contributor to within-industry skill upgrading. Regardless of the causal interpretation one attaches to the regressions reported in Tables 14 and 16, what does seem clear is that within-industry skill upgrading has been occurring in "high-tech" manufacturing industries. This pattern is quite clear at the two-digit SIC level. NSF data establish that Chemicals, Machinery, Electrical Equipment, Transportation Equipment and Professional and Scientific Instruments (SIC 28, and SIC 35–38) are R&D intensive industries, while BEA data show Tobacco, Printing, Chemicals, Stone Clay & Glass, Machinery, Electrical Equipment, Professional and Scientific Instruments, and parts of Transportation Equipment (SIC 21, 27, 28, 35, 36, 38, and 372–379) to be industries heavily investing in "high tech" equipment (i.e., more that 20 percent of 1987 investment is "high-tech investment.") These are the two-digit industries that show the most dramatic within-industry skill upgrading.

IV. Inside the Black Box

Other researchers have found evidence in favor of complementarity between educated or skilled labor and technological change, [Welch, 1970; Bartel and Lichtenberg, 1987; Mincer, 1989; Lillard and Tan, 1986; and Gill, 1990]. However, on the whole, these authors have not tried to use cross sectional relationships to explain the growth of skill differentials over the 1980s.[30] Some recent work does explicitly examine the extent to which technological change might explain increases in the demand for skilled labor. Mincer [1991] reports on time series regressions in which he included both supply and demand measures. Mincer's estimates imply an

[30] In fact, there is no reason to believe that patterns that exist across industries at a point in time should necessarily predict patterns of change within-industry (Mincer [1991] makes the same point).

important role for technology in explaining recent increases in the returns to education. At the same time, as Mincer acknowledges, the limited information available in time series raises questions about the robustness of the inferences drawn. In other work, Berndt, Morrison and Rosenblum [1992] use the Bureau of Economic Analysis (BEA) data available by two digit industries to examine the impact of investments in "high tech" capital on the demand for skilled labor. They regress the non-production share in total employment on a capital intensity measure and a measure of the share of high tech capital in total capital industry dummies and a time trend. Their estimates imply both capital-skill complementarity and complementarity of "high tech" capital and skills.

More qualitative information supports the notion that production labor-saving technological change has an important role in explaining the decline in production workers' share in wages. Work conducted by the BLS Office of Productivity and Technology [Mark, 1987] often mentions innovations that have lowered or are expected to lower production labor requirements.[31] The initial report [U.S. Department of Labor, 1966] summarizes studies of a large number of industries: "technological changes will continue to reduce the proportion of jobs involving primarily physical and manual ability and increase the need for jobs requiring ability to work with data and information."

It is striking how often reports on industries that show large shifts away from production labor mention innovations that are credited with substantially shifting the composition of labor demand. For example, when describing trends in aerospace (SIC 372 and 376) Bell [U.S. Department of Labor, 1986] writes, "New production methods are reducing requirements for a wide range of production workers while increasing the demand for highly educated and skilled professional and technological workers." The report goes on to discuss the introduction of numerically controlled and computer numerically controlled machines, industrial robots and flexible manufacturing systems. Similarly, when describing trends in Printing and Publishing (SIC 27) Critchlow [U.S. Department of Labor, 1982b] writes of "electronic composition shifting almost all composition and keyboarding to professional and clerical employees, bypassing typesetting employees altogether." Critchlow also men-

[31] A summary of these studies is available from the authors on request.

tions "bundling and handling machines that drastically reduce labor requirements within newspaper publishing." Similarly, the report on the electronics industry [U.S. Department of Labor, 1982a] mentions a large number of innovations that have reduced labor requirements, especially on manual tasks. In writing about the micro-electronics industry in particular, Alic and Harris (1986) report, "Technological advance has contributed to the shift toward skilled and professional jobs in the United States. Demand for technicians and other non-production workers has risen with each succeeding generation of more sophisticated (and expensive) fabrication equipment."

A 1988 survey of manufacturing technologies also contains useful information [U.S. Bureau of the Census, 1989b]. The survey of over 10,000 establishments was designed to be representative of manufacturing establishments classified in SIC 34–38. The survey questionnaire was designed to obtain reliable measures of prevalence of selected advanced technologies. Within establishments of 500 or more employees, 83 percent used computer aided design (CAD) or computer aided engineering (CAE), 70 percent used numerically controlled or computer numerically controlled machines, 36 percent used flexible manufacturing cells or systems, 43 percent used robots etc. Clearly, computer aided technologies are widely diffused within durable goods manufacturing. Not all of these technologies could be expected to decrease labor requirements for production workers. For example, CAD/CAE reduces the demand for draftsmen. Nevertheless, many could reasonably be expected to be production labor-saving rather than production labor using. Analyzing these data Dunne and Schmitz (1992) found that non-production worker's share in total employment was 2.5 percentage points lower in plants using three or more advanced technologies than plants using no such technologies. This coefficient implies that adoption of these "advanced" technologies can explain a substantial fraction of the move away from production workers that occurred during the 1970s and 1980s.[32]

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[32] Applying Dunne and Schmitz's reported coefficients on the technology variables (column 1, Table 6) to the means they report in Table 1 suggest that advanced technologies can explain a 1.6 percentage point rise in non-production workers' share in employment. The actual within-industry rise for SIC 34–38 was 4.2 percentage points for the 1979–1987 period and 5.4 percentage points for the 1973–1987 period. 1.6 is 38 percent of 4.2 and 30 percent of 5.4. These estimates are actually conservative in the sense that the means used in the calculation are means across establishments. Means across individuals would show substantially higher use of advanced technologies, since the correlation between establishment size and technology use is quite high.

It seems plausible that not only process innovations but also product innovations have been important in shifting labor demand away from production to non-production labor. Patent data show that the majority of innovations represent product, not process innovations. What is more, some of the industries that show some of the most dramatic shifts in the composition of the work force are those that have witnessed dramatic product innovations. For example, the move within the telecommunications industry away from the production of electromechanical towards the production of microelectronic devices has meant a dramatic drop in production labor requirements [Stowsky, 1988].

Taken together, evidence from all of these sources on individual technological innovations supports the notion that most of them were both labor-saving in general and production labor-saving in particular.

V. Conclusion

Both the quantitative and qualitative information we have assembled argues for the importance of biased technological change in explaining skill upgrading within U.S. manufacturing. While both the defense buildup and the changes in the nature and extent of international trade no doubt had some effect on the composition of employment within manufacturing, the magnitudes of these effects are not large enough to explain the bulk of the skill upgrading we observe. Furthermore, the strong correlation that we find between both R&D and computer investments and skill upgrading supports the notion that biased technological change is an important part of the explanation.

It is important to note what these results do and do not imply. Blue collar and less educated workers are over-represented in Manufacturing—as of 1987, 23 percent of those with not more than a high-school education, but only 14 percent of those with a college education were employed in manufacturing. Thus, developments that affect manufacturing's share in total employment will have relatively large effects on the skill composition of demand for labor. What our results do suggest is that the bulk of skill upgrading that occurred within manufacturing cannot be attributed to trade. This is striking for two reasons. First, as Murphy and Welch (1991) have argued, over 20 percent of the total skill upgrading that occurred over the

1980s occurred in manufacturing. Second, manufacturing is one of the sectors of the economy for which trade and foreign outsourcing are important. If trade and foreign outsourcing are not sufficient to explain the bulk of the skill upgrading that we observe in manufacturing, it seems plausible that trade cannot explain much skill upgrading in other branches of the economy.

We have argued that skill biased technological change accounts for a large fraction of the skill upgrading we have observed in manufacturing. To some extent the adoption of new technology may represent a response to increased competitive pressures—competitive pressures that might have increased both because of a changed regulatory environment and because of increased foreign competition. Alternatively one might imagine that the changes simply reflect the increased availability of labor-saving technology. We have not tried to sort out these explanations.

While a detailed analysis of the period before 1959 goes beyond the scope of this paper [see Delehanty (1968) for a detailed discussion of the 1950's], it is interesting to put the period we analyze within a somewhat larger historical context. Though the ASM data that we use go back only to 1958, published ASM, Census of Manufacturing and the BLS employer survey data go back earlier. All show quite dramatic shifts away from production labor during the 1950s[33] —a decade during which imports represented a small and stable fraction of manufacturing shipments, Defense Department procurements as a fraction of shipments actually fell, capital intensity within manufacturing remained constant, and skill premia as measured by the college high-school wage differential rose in the face of rising supplies of college graduates [Becker, 1975; Coleman, 1992; Goldin and Margo, 1992]. While these trends would seem to support the notion that historically, biased technological change has been an important source of the outward shift in demand for educated/skilled labor, they also suggest that we avoid exaggerating the uniqueness of the computer revolution.

33 For example the Census of Manufacturing shows the share of non-production workers in total employment rose more than 10 percentage points from 16.6 percent to 27.1 percent between 1947 and 1958.

References

Abowd, John. (1991). "Appendix: The NBER Trade and Labor Markets File." In J. Abowd and R. Freeman (eds.), *Immigration, Trade and the Labor Market.* Chicago: University of Chicago Press, pp. 407–421.

Alic, John A. and Martha Caldwell Harris, (1986) "Employment Lessons from the Electronics Industry." *Monthly Labor Review*, 109(February):27-36.

Bartel, Ann P. and Frank R. Lichtenberg. (1987). "The Comparative Advantage of Educated Workers in Implementing New Technology," *Review of Economics and Statistics* 69(February):1-11.

Becker, G. S. (1975). *Human Capital*, 2nd ed., Chicago University Press.

Berndt, Ernst R., Catherine J. Morrison, and Larry S. Rosenblum. (1992). "High-Tech Capital Formation and Labor Composition in U.S. Manufacturing Industries: An Exploratory Analysis." Paper presented in honor of Zvi Griliches' 60th birthday, Jerusalem, May 1991, NBER Working Paper No. 4010.

Blackburn M. L., D. E. Bloom, and R. B. Freeman. (1990). "The Declining Economic Position of Less-Skilled American Males." In G. Burtless (ed.), *A Future of Lousy Jobs?* Washington, D.C.: Brookings.

Bound, John and George Johnson. (1989). "Changes in the Structure of Wages During the 1980s: An Evaluation of Alternative Explanations." *American Economic Review.* 82(June): 371-392.

Coleman, Mary T., "Movement in the Earnings-Schooling Relationship", forthcoming, *Journal of Human Resources.*

Delehanty, George E., (1968) *Nonproduction Workers in U.S. Manufacturing*, North-Holland Publishing Company, Amsterdam.

Dickens, William T. (1988). "The Effects of Trade on Employment: Techniques and Evidence." In Tyson, Dickens, and Zysman (eds.), *The Dynamics of Trade and Employment*, Ballinger Publishing Company, pp. 41–85.

Dunne, Timothy and James A Schmitz, Jr. (1992), "Wages, Employer Size-Wage Premia and Employment Structure: Their relationship to Advanced-Technology Usage in U.S. Manufacturing Establishments", Manuscript, Federal Reserve Bank of Minneapolis.

Gill, Indermit S. (1990). "Technological Change, Education, and Obsolescence of Human Capital: some Evidence for the U.S., mimeograph, State University of New York at Buffalo.

Goldin, Claudia and Robert A. Margo. (1992) "The Great Compression: The Wage Structure in the United States at mid-century." *Quarterly Journal of Economics* 107(February):1-34.

Gray, Wayne. (1989). *Productivity Database.* NBER mimeo.

Gray, Wayne. (1992) *Upgrading Productivity Data Through 1989.* NBER mimeo.

Gorman, John A., John C. Musgrave, Gerald Silverstein and Kathy Comins. (1985) "Fixed Private Capital in the United States," *Survey of Current Business*, 65:7, July, 36-55.

Griliches, Zvi. (1969). "Capital-Skill Complementarity," *The Review of Economics and Statistics* 51(November):465–468.

Griliches, Zvi. (1970). "Notes on the Role of Education in Production Functions and Growth Accounting." In W. Lee Hansen (ed.), *Education, Income and Human Capital: Studies in Income and Wealth, 35*, New York: Columbia University Press for the National Bureau of Economic Research.

Gullickson, William and Michael J. Harper, (1987) "Multifactor Productivity in U.S. Manufacturing, 1949-1983," *Monthly Labor Review*, 110(October): 18-28.

Katz, Lawrence F. and Kevin Murphy. (1992). "Changes in Relative Wages, 1963–1087: Supply and Demand Factors," *Quarterly Journal of Economics*, Cambridge, Massachusetts: MIT Press, 107(February):35–78.

Katz, Lawrence F. and Ana Revenga. (1989), "Changes in the Structure of Wages: The U.S. vs. Japan," *Journal of Japanese and International Economics*, III: 522-553.

Lillard, Lee A. and Hong W. Tan. (1986). *Private Sector Training: Who Gets It and What Are Its Effects*. Santa Monica, California, The Rand Corporation, March.

Mark, Jerome S., (1987) "Technological Change and Employment: Some Results from BLS Research," *Monthly Labor Review*, 110(April):26-29.

Mincer, Jacob. (1989). "Human Capital Responses to Technological Change in the Labor Market," NBER Working Paper No. 3207.

Mincer, Jacob. (1991). "Human Capital, Technology, and the Wage Structure: What Do Time Series Show?". NBER Working Paper No. 3581.

Murphy, Kevin M. and Finis Welch. (1992). "The Structure of Wages," *Quarterly Journal of Economics*, Cambridge, Massachusetts: MIT Press, 107(February):285-326.

Murphy, Kevin M. and Finis Welch. (1992). "Industrial Wages and the Rising Importance of Skill," in Sheldon H. Danziger and Peter Gottschalk (ed.), *Uneven Tides: Rising Inequality in America.*

Murphy, Kevin M. and Finis Welch. (1989). "Wage Premiums for College Graduates: Recent Growth and Possible Explanations," *Educational Researcher*, May.

Musgrave, John C. (1986) "Fixed Reproducible Tangible Wealth in the United States: Revised Estimates," *Survey of Current Business*, 66:1, January, 51-75.

National Science Foundation. (1991), *Selected Data on Research and Development in Industry: 1989.*

Revenga, Ana L. (1992) "Exporting Jobs? The Impact of Import Competition on Employment and Wages in U.S. Manufacturing," *Quarterly Journal of Eco-*

nomics 107(February):255–284.

Scherer, Frederic M. (1984). "Using Linked Patent and R & D Data to Measure Interindustry Technology Flows." In Zvi Griliches (ed.), *R & D, Patents and Productivity*, Chicago: University of Chicago Press.

Donald Siegel, and Zvi Griliches (1992). "Purchased Services, Outsourcing, Computers and Productivity in Manufacturing", pp. 429-460, in Zvi Griliches (ed), *Output Measurement in the Service Sector; Studies in Income and Wealth, Vol. 56*, The University of Chicago Press, Chicago.

Stowsky, Jay S. (1988). "The Domestic Employment Consequences of Trade in Telecommunications Equipment." In Tyson, Dickens, and Zysman (eds.), *The Dynamics of Trade and Employment*, Ballinger Publishing Company, pp. 205–236.

U.S. Bureau of the Census. (1981). *Current Industrial Reports* Shipments to Federal Government Agencies, 1980, U.S. Government Printing Office, Washington.

U.S. Bureau of the Census. (1986). *1982 Census of Manufactures.* U.S. Government Printing Office, Washington.

U.S. Bureau of the Census. (1989a). *The Relationship Between the 1970 and 1980 Industry and Occupation Classification Systems.* Prepared by Paula L. Vines and John A. Priebe.

U.S. Bureau of the Census. (1989b). *Current Industrial Reports* Manufacturing Technology 1988, prepared under the direction of Gaylord Worden, U.S. Government Printing Office, Washington.

U.S. Bureau of the Census. (1991). *Census of Manufactures 1987, MC87-S-7, Subject Series*, Manufacturers Shipments to the Federal Government. U.S. Government Printing Office, Washington.

U.S. Department of Labor, (1966), B.L.S. Bulletin 1474. "Technological Trends in Major American Industries". Written under the supervision of John Macut and John Shott by Robert Adams, Robert Ball, Robert Barry, Gordon Chapman, Audrey Freedman, Arthur Herman, Richard Johnson, Stephen Keyes, Richard Lyon, Richard Riche and Rose Zeisel.

U.S. Department of Labor, (1982a), B.L.S. Bulletin 2104. "The Impact of Technology on Labor in Four Industries: Meat Packing/Foundries/ Metalworking Machinery/Electrical and Electronic Equipment," written under the supervision of John J. Macut, Chief, Division of Technological Studies. Industry reports were written under the supervision of Richard W. Riche, and Rose N. Zeisel. Authors: Robert V. Critchlow (electrical and electronic equipment), Gary E. Falwell (meat products), Richard W. Lyon foundries), and A. Harvey Belitsky (metal working machinery).

U.S. Department of Labor, (1982b), B.L.S. Bulletin 2137. "The Impact of Technology on Labor in Five Industries: Printing and publishing/Water Transportation/ Copper Ore Mining/Fabricated Structural Metal/Intercity Trucking," written under the supervision of John J. Macut, Chief, Division of Technological Studies, Richard W. Riche, and Rose N. Zeisel. Final stages of preparation took place in Division of Industry Productivity Studies, Charles W. Ardolini, Chief. Authors: Robert V. Critchlow (printing/publishing, water trans.), Richard W. Lyon (copper), Charles L. Bell (fab. struct. metal), and A. Harvey Belitsky (trucking).

U.S. Department of Labor, (1986), B.L.S. Bulletin 2242. "Technology and Its Impact on Labor in Four Industries: Tires/Aluminum/Aerospace/Banking," U.S. written under supervision of Rose N. Zeisel and Richard W. Riche, by A. Harvey Belitsky (tires), Richard W. Lyon (aluminum), Charles L. Bell (aerospace), and Robert V. Critchlow (banking).

U.S. International Trade Commission, (1982), *Summary of Trade and Tariff Information: Semiconductors*, Publication # 841, U.S. Government Printing Office, Washington.

U.S. International Trade Commission, (1988), *Imports under Items 806.30 and 807.00 if the Tariff Schedules of the United States. 1984-1987*, Publication # 2144, U.S. Government Printing Office, Washington.

Welch, Finis R. (1970). "Education in Production," *Journal of Political Economy* 78(January/February):35-59.

Table 1: Occupational Distributions within Manufacturing by Year

	1973	1979	1987
White Collar	28.6%	31.9%	37.2%
Manager	27.0	27.0	29.4
Professional	18.8	19.9	21.5
Technician	8.7	9.0	9.0
Sales Worker	7.3	7.5	8.8
Clerical Worker	38.1	36.6	31.4
Subtotal	100.0	100.0	100.0
Blue Collar	71.4%	68.1%	62.8%
Craft	24.4	25.7	30.3
Operative	62.3	61.6	57.6
Laborer	9.8	9.5	9.0
Service Worker	3.0	2.8	2.6
Agricultural Labor	0.5	0.5	0.6
Subtotal	100.0	100.0	100.0

Source: CPS, May 1973, Outgoing Rotations, 1979 and 1987.

Table 2: Production, Non-Production and Central Office Employment

	1973	1979	1987
Total Non-Production	28.3%	30.9%	35.4%
Percent in Central Offices	17.3%	19.7%	18.4%

Source: Annual Survey of Manufacturing.

Table 3: Educational Attainment of the Manufacturing Work Force

	% High-School Graduates			% At Least Some College		
	1973	1979	1987	1973	1979	1987
Managerial and Professional	92.8	94.9	97.5	63.5	70.6	77.6
Sales	86.4	85.9	93.4	61.0	60.1	69.6
Clerical	84.9	88.3	92.0	23.8	30.2	35.3
Blue-Collar	52.9	61.3	70.3	9.3	13.1	16.8
Total	64.3	71.1	79.7	21.4	26.5	34.3

Source: CPS, May 1973, Outgoing Rotations, 1979, 1987.

Table 4: Skill Upgrading Within Manufacturing

	Occupation		Education	
	1973–1979	1973–1987	1973–1979	1973–1987
Total	2.50	6.33	4.34	9.31
White Collar	1.57	4.58	4.27	9.34
Blue Collar	0.77	2.19	2.83	5.58
Within	1.03	2.97	3.30	6.81
% Within	41%	47%	76%	73%

Source: CPS, May 1973, Outgoing Rotations, 1979 and 1987.

Note: Numbers represent 100 times the increase in predicted log hourly earnings using either the broad occupational categories listed in Table 1 or single years of education as co-variates.

Table 5: Possible Contributors to the Increased Relative Demand for Skilled Labor

	row	1959	1973	1979	1987
R&D Expenditures as a Fraction of Manufacturing Shipments					
Total	[1]	2.6	2.4	2.2	3.9
Privately Funded	[2]	1.6	0.9	0.7	1.3
Government Funded	[3]	1.1	1.5	1.5	2.6
Share of High Tech Capital in Total Manufacturing Capital Stock					
Total	[4]	1.0	1.4	3.3	6.9
Computing Eq.	[5]	0.3	0.2	0.5	2.3
Communications Eq.	[6]	0.2	0.3	0.6	2.2
Scientific Eq.	[7]	0.5	0.6	1.3	1.2
Photocopy Eq.	[8]	0.0	0.3	1.0	1.2
Imports and Exports as a Fraction of Manufacturing Shipments					
Exports	[9]	4.5	8.4	10.6	10.7
Imports	[10]	4.2	8.2	12.3	17.3
Defense Department Purchases as a Fraction of Manufacturing Shipments					
Purchases	[11]	5.9	2.1	2.0	4.2

Sources: Rows 1-3, National Science Foundation (1991) and ASM; Rows 4-8, unpublished tabulations, Bureau of Economic Analysis; Rows 9-11 National Income and Products Accounts and ASM.

Table 6: Industry/Sector Decompositions of the Rise in the Share of Non-production Workers

	Employment		Wages	
	Between	Within	Between	Within
		1959–1973		
	−.009	.078	−.018	.069
Total		.069		.051
		1973–1979		
	.112	.187	.085	.208
Total		.299		.293
		1979–1987		
	.165	.387	.306	.468
Total		.552		.774

Note: All calculations have been annualized.

Table 7: Industry-Sector Decompositions of the Rise in the Share of Non-production Workers

	Employment		Wages	
	Between	Within	Between	Within
1959-1973				
Imports	.007	-.001	.005	.001
Exports	.010	.002	.012	.003
Domestic Consumption	-.026	-.076	-.035	.067
	-.009	.078	-.018	.069
Total		.069		.051
1973-1979				
Imports	.001	-.006	-.007	-.002
Exports	.021	.007	.028	.004
Domestic Consumption	.089	.186	.064	.206
	.112	.187	.085	.208
Total		.299		.293
1979-1987				
Defense	.072	.014	.101	.004
Imports	.029	-.002	-.024	-.006
Exports	.019	.014	.035	.014
Domestic Consumption	.044	.361	.193	.456
	.165	.387	.306	.468
Total		.552		.774

Note: A calculation for the defense sector is possible only for the 1979--1987 period. It's contribution in earlier periods is included in the domestic consumption term. All calculations have been annualized.

Table 8: Individual Sector-Industry Cells with Large "Between" Effects, 1979–1987

SIC	Industry	100 x $\Delta S_i^d(\bar{S}_{n_i} - \bar{S}_n^c)$	100 x ΔS_i^d	$\bar{S}_{n_i}$	Emp^d 1979
Defense					
3662	Telecommunications, Radio & TV	.047	.184	62.3	41.1%
3721	Aircraft	.013	.077	53.1	34.9
3728	Aircraft Parts & Equipment, nec	.008	.069	48.8	27.9
3761	Guided Missiles & Space Vehicles	.025	.076	69.0	70.9

SIC	Industry	100 x $\Delta S_i^m(\bar{S}_{n_i} - \bar{S}_n^c)$	100 x ΔS_i^m	$\bar{S}_{n_i}$	I/Y 1979
Imports					
3573	Computers	−.017	−.049	71.8	7.9%
3674	Semiconductors	−.011	−.043	62.3	30.2
3711	Motor Vehicles & Car Bodies	.009	−.053	20.0	22.4
2033	Canned Fruits & Vegetables	.006	−.038	21.6	5.1
3149	Footwear, except rubber, nec	.006	−.048	24.4	105.1
3574	Calculating & Accounting Machines	−.008	−.032	62.1	68.2

SIC	Industry	100 x $\Delta S_i^x(\bar{S}_{n_i} - \bar{S}_n^c)$	100 x ΔS_i^x	$\bar{S}_{n_i}$	X/Y 1979
Exports					
3573	Computers	.011	.030	71.8	26.4%
3721	Aircraft	.015	.090	53.1	37.1

SIC	Industry	100 x $\Delta S_i^c(\bar{S}_{n_i} - \bar{S}_n^c)$	100 x ΔS_i^c	$\bar{S}_{n_i}$	R/Y 1979
Domestic Consumption					
2711	Newspaper Publishing	.012	.046	63.5	100.1%
2721	Periodicals	.018	.034	88.3	97.9
3312	Blast Furnaces & Steel Mills	.035	−.267	23.5	124.8
3573	Computers	.038	.107	71.8	78.7
3662	Telecommunications, Radio & TV	.011	.043	62.3	58.2
3674	Semiconductors	.021	.083	62.3	100.6
3679	Electronic Components, nec	.011	.102	47.1	87.7
3721	Aircraft	−.019	−.115	53.1	30.7

Note: Industries included for defense, imports or exports if $|\Delta S_i(\bar{S}_{n_i} - \bar{S}_n^c)| \geq 0.005$.
Industries included for the residual sector if $|\Delta S_i(\bar{S}_{n_i} - \bar{S}_n^c)| \geq 0.010$.

Table 9: Top Contributions to within Industry Skill Upgrading

Industry	SIC	$S \times \Delta S_n$	ΔS_n	$\bar{S}_n$	D/Y	I/Y	X/Y	C/I
Newspaper Publishing	2711	0.017	0.859	63.5	0.0	0.1	0.5	13.8
Commercial Printing	2752	0.008	0.452	33.7	0.0	0.5	1.3	5.1
Blast Furnaces & Steel Mills	3312	0.007	0.277	23.5	0.0	11.8	3.0	1.9
Farm Machinery & Equipment	3523	0.006	1.011	36.5	0.0	15.3	13.6	3.8
Construction Machinery	3531	0.009	1.061	38.4	1.0	5.0	35.1	8.7
Special Industry Machinery, nec	3559	0.006	1.281	49.0	0.0	10.7	24.1	13.2
Computers	3573	0.021	1.048	71.8	2.8	7.9	26.4	23.0
Industrial Machinery, nec	3599	0.007	0.552	31.1	0.0	10.7	24.1	13.2
Telecommunications: Telephone	3661	0.053	7.020	67.7	1.6	3.3	4.6	18.9
Telecommunications: Radio & TV	3662	0.022	0.685	62.3	41.1	9.0	9.7	20.0
Semiconductors	3674	0.010	0.982	62.3	1.5	30.2	28.1	8.9
Electric Components, nec	3679	0.011	1.037	47.1	3.5	8.5	17.3	10.5
Motor Vehicle Parts & Accessories	3714	0.006	0.205	23.7	0.0	9.6	12.7	2.8
Aircraft	3721	0.011	0.525	53.1	34.9	2.7	37.1	15.1
Aircraft Engines & Parts	3724	0.006	0.581	48.6	40.3	6.0	15.9	11.3
Ship Building & Repair	3731	0.006	0.687	29.9	32.1	0.0	2.9	4.6
Railroad Equipment	3743	0.007	2.320	35.2	0.0	5.5	5.1	13.2
average		0.001	0.445	34.9	1.7	12.7	9.1	6.5
weighted average			0.468	38.5	3.5	8.1	9.3	6.3

Note: Industries Included if $|S \times \Delta S_n| \geq 0.006$.

Notes:

c/i: 100 x computers as a share of total investments as in 1987

x/y: 100 x exports/shipments, as of 1979

i/y: 100 x imports/shipments, as of 1979

d/y: 100 x shipments to the department of defense/total shipments as of 1979

Table 10: Four Digit SIC Variable Means

	1959–1973	1973–1979	1979–1987
d S_N	0.069	0.208	0.468
d ln(K)	4.201	3.127	2.807
d ln(P)	3.662	1.916	1.361
d ln(E)	4.670	3.868	3.493
d ln(Y)	3.892	2.115	1.694
d ln(K/Y)	0.309	1.012	1.113
d ln(P/Y)	-0.230	-0.200	-0.333
d ln(E/Y)	0.778	1.753	1.800

Source: Authors' tabulations based on the Annual Survey of Manufacturing.
Sample: 450 four-digit manufacturing industries
Notes: Data weighted by average share of industry wage bill in manufacturing.

Variable	Description
d S_N	100 x the Annual Change in the Non-Production Workers Share in the Wage Bill
d ln(K)	100 x the Annual Change in the log of the Capital Stock
d ln(P)	100 x Annual Change in the log of Plant
d ln(E)	100 x Annual Change in the log of Equipment
d ln(Y)	100 x Annual Change in the log of Real Output
d ln(K/Y)	d ln(K) - d ln(Y)
d ln(P/Y)	d ln(P) - d ln(Y)
d ln(E/Y)	d ln(E) - d ln(Y)

Table 11: Changes in the Non-Production Workers' Share in the Wage Bill, 1979–1987

[Dependent Variable: Annual Change in Non-production Workers' Share in the Total Wage Bill]

Equation	(1)	(2)	(3)	(4)
d ln(K/Y)	0.028		0.064	
	(0.008)		(0.011)	
d ln(P/Y)		-0.019		0.025
		(0.011)		(0.016)
d ln(E/Y)		0.046		0.041
		(0.012)		(0.012)
d ln(Y)			0.035	0.038
			(0.008)	(0.010)
Constant	0.437	0.378	0.337	0.338
	(0.035)	(0.041)	(0.041)	(0.042)
R^2	0.028	0.042	0.070	0.072
$\hat{\sigma}$	0.711	0.706	0.696	0.696

Source: Authors' tabulations based on the Annual Survey of Manufacturing.

Sample: 450 four-digit manufacturing industries.

Notes: Equations weighted by average share of industry wage bill in manufacturing.

Table 12: Changes in the Non-Production Workers' Share in the Wage Bill, 1959–1973, 1973–1979, and 1979–1987, Combined
[Dependent Variable: Annual Change in Non-production Workers' Share in the Total Wage Bill]

Equation	(1)	(2)	(3)	(4)	(5)
d ln(K/Y)		0.014 (0.003)		0.038 (0.005)	
d ln(P/Y)			-0.022 (0.006)		0.003 (0.008)
d ln(E/Y)			0.035 (0.006)		0.033 (0.006)
d ln(Y)				0.027 (0.004)	0.025 (0.005)
1973–1979	0.139 (0.035)	0.129 (0.035)	0.105 (0.035)	0.160 (0.035)	0.150 (0.036)
1979–1986	0.399 (0.035)	0.389 (0.035)	0.361 (0.036)	0.427 (0.035)	0.420 (0.037)
Constant	0.069 (0.025)	0.065 (0.025)	0.037 (0.025)	-0.047 (0.030)	-0.052 (0.031)
R^2	0.029	0.099	0.113	0.125	0.129
$\hat{\sigma}$	0.531	0.528	0.524	0.521	0.520

Source: Authors' tabulations based on the Annual Survey of Manufacturing.

Sample: 450 four-digit manufacturing industries.

Notes: Equations weighted by average share of industry wage bill in manufacturing.

Table 13: Computes as a Share of Total Investments

Equation	Means	Correlations			
	(1)	(2)	(3)	(4)	(5)
C/I_{77}	2.79%	0.14	1.00		
C/I_{82}	3.92	0.20	0.83	1.00	
C/I_{87}	7.49	0.33	0.55	0.71	1.00
		dS_N	C/I_{77}	C/I_{82}	C/I_{87}

Source: Authors' tabulations based on the Annual Survey of Manufacturing supplemented with information on computer investments drawn from the Census of Manufacturing.

Sample: 450 four-digit manufacturing industries.

Notes: Equations weighted by average share of industry wage bill in manufacturing. All equations include $d\ ln(P/Y)$, $d\ ln(E/Y)$ and $d\ ln(Y)$.

Table 14: Effect of Computer Investment on the Change in the Non-Production Workers' Share in the Wage Bill, 1979–1987

[Dependent Variable: Annual Change in Non-production Workers' Share in the Total Wage Bill]

Equation	(1)	(2)	(3)	(4)
C/I 1977	0.019			−0.002
	(0.008)			(0.009)
C/I 1982		0.031		
		(0.009)		
C/I 1987			0.032	0.033
			(0.005)	(0.006)
R^2	0.083	0.095	0.143	0.143
$\hat{\sigma}$	0.693	0.688	0.669	0.670

Source: Authors' tabulations based on the Annual Survey of Manufacturing supplemented with information on computer investments drawn from the Census of Manufacturing.

Sample: 450 four-digit manufacturing industries.

Notes: Equations weighted by average share of industry wage bill in manufacturing. All equations include $d\ ln(P/Y)$, $d\ ln(E/Y)$ and $d\ ln(Y)$.

Table 15: R&D Expenditures in 1974 as a Share of Shipments in 1974

	Means	Correlations			
Equation	(1)	(2)	(3)	(4)	(5)
dS_N	0.40%	1.00			
R&D					
Industry of Origin	1.07%	0.53	1.00		
Industry of Use	0.43	0.20	0.54	1.00	
C/I_{87}	7.36	0.57	0.44	0.09	1.00
		dS_N	Origin (R&D)	Use (R&D)	C/I_{87}

Source: Authors' tabulations based on the Annual Survey of Manufacturing supplemented with information on computer investments drawn from the Census of Manufacturing and data on R&D expenditures kindly provided by Professor Scherer.

Sample: 143 three-digit manufacturing industries.

Notes: Equations weighted by average share of industry wage bill in manufacturing. All equations include $d\ ln(P/Y)$, $d\ ln(E/Y)$ and $d\ ln(Y)$.

Table 16: The Impact of R&D Investments on Changes in the Wage Bill Share of Non-Production Workers, 1979–1987
[Dependent Variable: Annual Change in Non-production Workers' Share in the Total Wage Bill]

Equation	(1)	(2)	(3)	(4)	(5)
R&D					
Industry of Origin	0.095			0.080	
	(0.022)			(0.021)	
Industry of Use		0.119			0.122
		(0.060)			(0.054)
C/I_{87}			0.028	0.024	0.028
			(0.006)	(0.006)	(0.006)
R^2	0.408	0.346	0.420	0.476	0.440
$\hat{\sigma}$	0.355	0.373	0.351	0.335	0.346

Source: Authors' tabulations based on the Annual Survey of Manufacturing supplemented with information on computer investments drawn from the Census of Manufacturing and data on R&D expenditures kindly provided by Professor Scherer.

Sample: 143 three-digit manufacturing industries.

Notes: Regressions weighted by average share of industry wage bill in manufacturing. All regressions include $d\ ln(P/Y)$, $d\ ln(E/Y)$ and $d\ ln(Y)$.

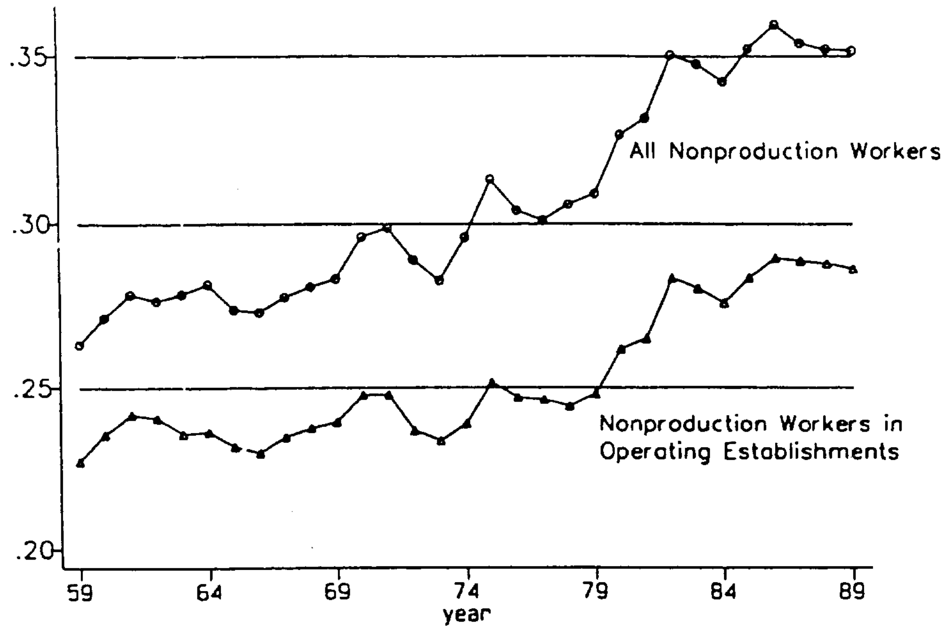

Figure 1: Non-Production Workers Share
in Total Employment

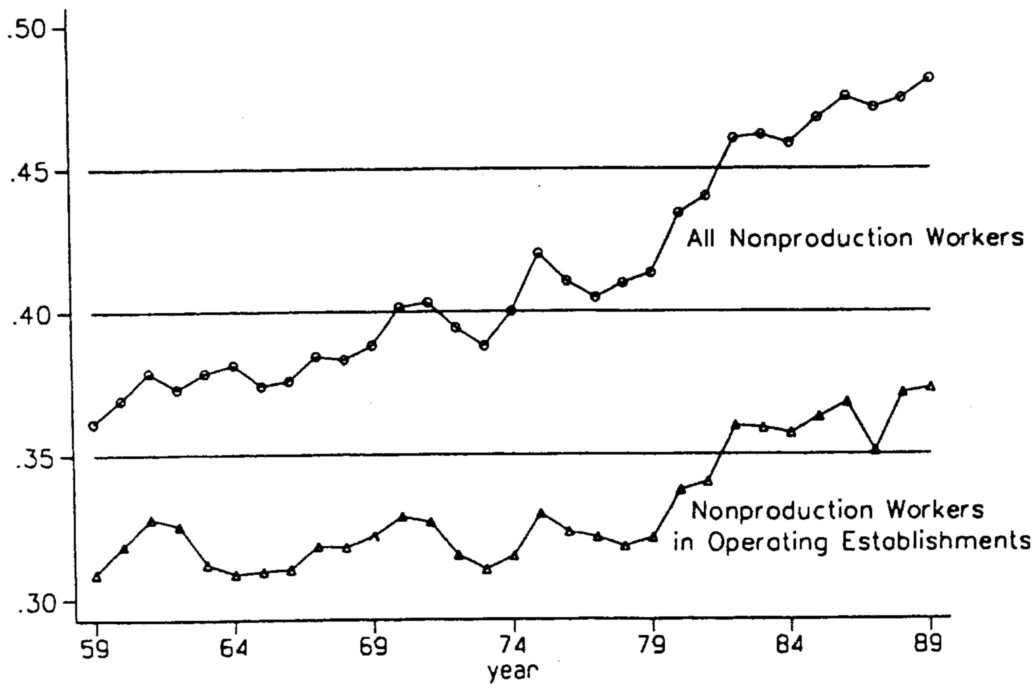

Figure 2: Non-Production Workers Share
in the Wage Bill

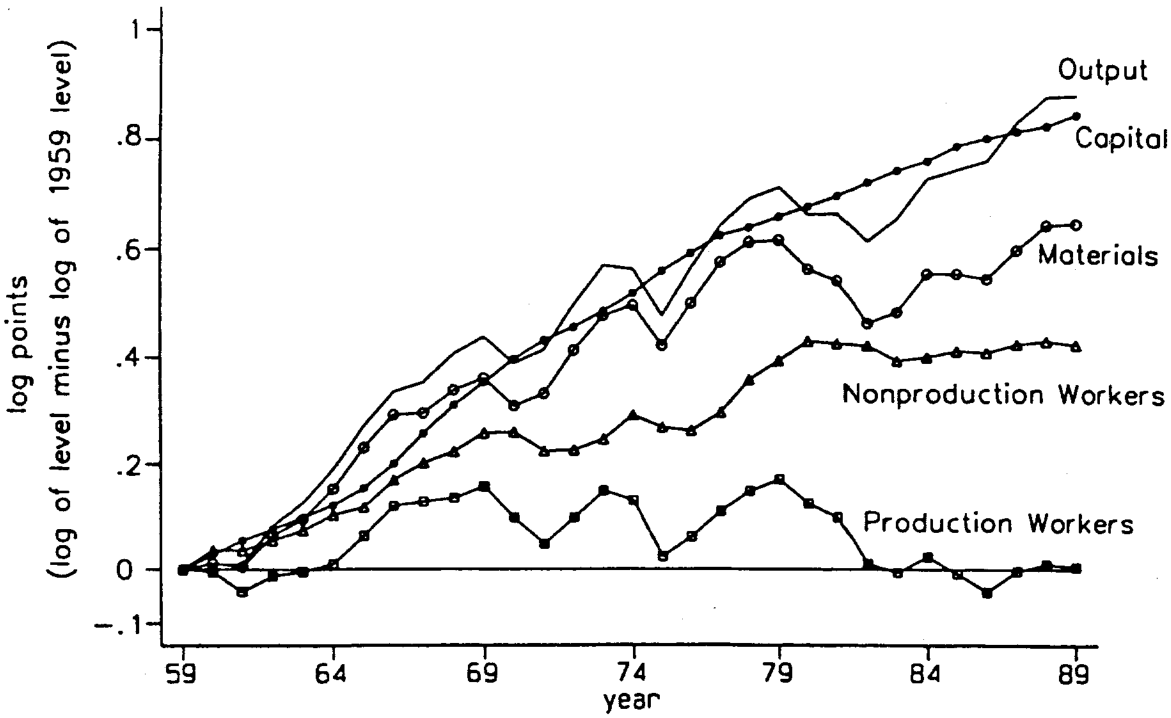

Figure 3: Output and Inputs in Manufacturing