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Abstract

This paper examines the role of skilled labor in the growth of total factor productivity. We use panel data from manufacturing industries within the United States to assess the extent to which productivity growth in yearly cross–sections of U.S. manufacturing industries is tied to industry shares of skilled labor inputs. We find evidence of an explosion in skilled–labor augmenting technological progress during the period from approximately 1973 to 1981, which coincides with a period of suddenly increasing wage inequality and rapid growth in the relative wages of educated and experienced workers. We also provide evidence from aggregate manufacturing data that confirm this shift pre– and post–1973.

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1. Introduction

Evidence is accumulating that the last 25 years has witnessed a dramatic change in the way goods are produced. Both anecdotal and systematic evidence suggests that during this period firms began to replace relatively unskilled workers by skilled workers and equipment at an unprecedented rate. This was not due to the increased availability of skilled labor, since both the relative wages and employment of skilled workers increased dramatically. This process is usually referred to as "skill–biased technical change," and is widely regarded as the primary factor behind the increased dispersion of the income distribution during the same time period.

In this paper we examine this phenomenon from another angle. Industries may differ in their receptiveness to increased knowledge, and consequently in their productivity growth rates. What we call "skilled–labor augmenting technical progress" attaches itself more readily to educated or experienced workers, and consequently to those industries that are more skilled labor–intensive. Improvements in electronics and computers, for example, presumably have a larger impact on the effective labor input of engineers and statisticians than of farm workers and janitors. Furthermore, since skilled labor–augmenting technical progress can induce skill–biased technical change—under conditions which we suggest are present in U.S. manufacturing—a finding of skilled labor–augmenting technical progress could "explain" the acceleration of skill–biased technical change. In any case, it offers additional independent evidence of unusual structural change during roughly the same time period.

We examine the extent of skilled labor–augmenting technical progress in U.S. manufacturing over the period 1958–1991.[1] We can measure the extent to which industries differ in skilled relative to unskilled labor input, and use that cross–sectional variation to identify the contribution of this phenomenon to overall growth. We find evidence of a sudden explosion in skilled–labor augmenting technological progress

[1] An earlier paper, Kahn and Lim (1994) is based on the same general idea.

during the period from approximately 1973 to 1981. This roughly coincides with a period of suddenly increasing wage inequality, as well as rapid growth in wages of young educated workers. Since one of our measures of skill level is related to years of schooling, we can also claim to have controlled at least to some extent for growth in human capital.

We also find little consistent evidence of an association of productivity growth with industry shares of other inputs such as capital, or more specifically, capital equipment, even after allowing for technical progress only embodied in new equipment. This would seem to cast doubt on stories that stress plant retooling as the *sine qua non* of technical change during this time period. But there is some indication that the period of skilled labor–augmenting technical progress was immediately preceded by a shorter period of *regress*—as though the initial impact of technology were negative, a possibility that Hornstein and Krusell (1996) and others have argued for as a partial explanation for the productivity slowdown.

In addition to exploring the empirical relationship between skilled labor, output growth, and productivity growth, we also examine a completely separate set of evidence based on steady state implications of the technology with aggregate time series data. Somewhat surprisingly, these results corroborate the panel data findings with regard to skilled labor effects, even though they are based on a completely independent dimension of the data. They also provide the only evidence for similar effects from capital equipment.

2. The Model

2.1. Technology

We conceive of "knowledge" as an aggregate state variable that dictates the potential effective labor per worker as function of the worker's human capital. For convenience we follow the practice of others in this area and divide workers into two broad categories: "skilled" and "unskilled." (Obviously the ideas generalize to a more continuous classification.) What we call skilled labor–augmenting technical progress is an advance in knowledge that augments the effective labor of skilled workers by more than the effective labor of unskilled workers. For example, the development of advanced equipment that has the potential to replace unskilled labor with a smaller amount of skilled labor would fall into this category. [2]General (e.g. Hicks–neutral) technological progress, in contrast, adds to the effective labor of both skilled and unskilled alike.

Consider a set of industries indexed by i. Each of the industries uses physical capital (plant and equipment), unskilled labor, and skilled labor, to produce its output. Depending on the data requirements, we will specify production either in terms of value added or gross output. In the first case, a representative firm in industry i at date t has a constant returns to scale production technology that in its most general form we specify as:

$$Y_{it} = A_{it}F_i(K^p_{it}, K^e_{it}E_t, N^s_{it}H^s_t, N^u_{it}H^u_t), \tag{2.1}$$

where Y_{it} is value added, K^p_{it} is "plant," K^e_{it} is equipment, N^u_{it} is the number of unskilled workers at the firm, and N^s_{it} the number of skilled workers. In the second case, the production function is

$$Y^*_{it} = A_{it}F_i(K^p_{it}, K^e_{it}E_t, N^s_{it}H^s_t, N^u_{it}H^u_t, M_{it}X_t), \tag{2.2}$$

where Y^*_{it} is gross output, and M_{it} is a vector of material inputs. For the sake of exposition we will proceed using (2.1), as it should be clear how to apply the same analysis to (2.2).

The various terms multiplying the inputs represent increases in efficiency per

[2]As we shall see, however, this is not exactly the same thing as skill–biased technical change, which is an increase in the relative demand for skilled labor. This hinges on whether skilled labor's share increases or not.

measured unit of that input. Thus, for example, H_t^s represents the efficiency of skilled workers. In practice, of course, these terms can only be identified relative to some time when they are defined to be equal to one. Also, as will be clear below, that they are independent of i and that there is no efficiency term multiplying K^p represent identifying assumptions. We will discuss these and other issues surrounding the interpretation of these variables as we go along.

We assume that the firm is competitive, and faces market wages W_t^s and W_t^u (per unit of effective labor), rental prices of plant and equipment Q_t^p and Q_t^e, and market prices $\{P_{it}\}$. Note that the production function differs by industry, and that A_{it} has both an aggregate and idiosyncratic component. H_t and E_t, on the other hand, are purely aggregate. As will be clearer below, these are essentially a matter of definition.

2.2. Equilibrium

The firms face the following myopic optimization problem:

$$\underset{K_{ji},N_{ji}^s,N_{it}^u}{\text{Max}} \quad P_{it}A_{it}F_i(K_{it}^p, K_{it}^e E_t, N_{it}^s H_t^s, N_{it}^u H_t^u) - Q_t^p K_{it}^p - Q_t^e K_{it}^e - W_{it}^s H_{it} N_{it}^s - W_{it}^u N_{it}^u \quad (2.3)$$

Firms' optimality conditions yield that the payment to each input factor must be equal to its marginal revenue products. Thus we have,

$$\begin{aligned} P_{it}A_{it}F_{1i}(K_{it}^p, K_{it}^e E_t, N_{it}^s H_t^s, N_{it}^u H_t^u) &= Q_t^p \\ P_{it}A_{it}F_{2i}(K_{it}^p, K_{it}^e E_t, N_{it}^s H_t^s, N_{it}^u H_t^u) &= Q_t^e / E_t \\ P_{it}A_{it}F_{3i}(K_{it}^p, K_{it}^e E_t, N_{it}^s H_t^s, N_{it}^u H_t^u) &= W_t^s \\ P_{it}A_{it}F_{4i}(K_{it}^p, K_{it}^e E_t, N_{it}^s H_t^s, N_{it}^u H_t^u) &= W_t^u \end{aligned} \qquad \forall i,t \qquad (2.4)$$

The factor shares at each point in time are denoted α_{it}^k, where $k = p, e, s, u$. Constant returns to scale implies

$$\alpha_{it}^p = \frac{Q_t^p K_{it}^p}{P_{it} Y_{it}} = \frac{F_{1i}(\cdot) K_{it}^p}{F(\cdot)},$$

and similarly for the other factors. It is the variation in these factor shares across industries that will allow us to decompose productivity growth into skilled–labor augmenting and other components. We have

$$\begin{aligned}\Delta \ln Y_{it} \;&\cong\; \Delta \ln A_{it} + \alpha^{p}_{it}\Delta \ln K^{p}_{it} + \alpha^{e}_{it}(\Delta \ln K^{e}_{it} + E_t) \\ &\quad \alpha^{s}_{it}(\Delta \ln N^{s}_{it} + \Delta \ln H^{s}_{t}) + \alpha^{u}_{it}(\Delta \ln N^{u}_{it} + \Delta \ln H^{u}_{t})\end{aligned} \tag{2.5}$$

which implies that total factor productivity (TFP) growth satisfies the following:

$$\begin{aligned}\Delta \ln TFP_{it} &= \Delta \ln Y_{it} - (\alpha^{p}_{it}\Delta \ln K^{p}_{it} + \alpha^{e}_{it}\Delta \ln K^{e}_{it} + \alpha^{s}_{it}\Delta \ln N^{s}_{it} + \alpha^{u}_{it}\Delta \ln N^{u}_{it}) \\ &= \Delta \ln A_{it} + \alpha^{e}_{it}\Delta \ln E_t + \alpha^{s}_{it}\Delta \ln H^{s}_{t} + \alpha^{u}_{it}\Delta \ln H^{u}_{t}.\end{aligned} \tag{2.6}$$

Thus an industry's value added TFP growth will depend in general on its equipment and skilled labor factor intensities, as well as the extent to which technical progress takes the form of growth in A, E, H^sor H^u.

Our empirical strategy is essentially to turn this idea on its head and estimate the relative importance of these components in any time period by the extent to which TFP growth cross–sectionally during that time is associated with these factor shares. We will also show that if the production technology is CES but not Cobb–Douglas, the system (2.4) can also be applied to aggregate time–series data to obtain alternative estimates of growth in the three components.

It should be noted that this approach in principle fails to distinguish between factor–augmenting technical progress and improvements in the quality of inputs. For capital this may not be an important distinction (presumably most changes in E are changes in input quality, though one can imagine increasing the productivity of a given piece of equipment). For labor, though, there is arguably a significant difference between the two—Klenow (1996) refers to the two phenomena as "ideas" and "human capital." For example, H^s could grow because workers themselves are better–educated, or because advances in knowledge affect their productivity relative to that of other inputs. Nonetheless, we will stick with the "ideas" interpretation, in part on the basis of evidence from education–based definitions of skill (which arguably control at least to some extent for human capital), and in part on the finding that H^s jumped rather sharply relative to any plausible measure of human capital in the skilled work force. Although in principle both knowledge and human capital are stocks, we would argue that a rapid increase in knowledge is more plausible than a rapid increase in overall human capital, since the former could, for example, come from the work of a single genius, while the latter requires educating the average worker.

3. Empirical Implementation

3.1. Data

Our data come from two main sources: The Current Population Survey (CPS) and the Annual Survey of Manufacturers (ASM). We make use of the CPS outgoing rotation data set and the manufacturing productivity (MP) database, both compiled by the National Bureau of Economic Research. From the CPS outgoing rotation survey we have data on individual workers' industry, education level, and earnings, annually over the period 1979–1991. We then construct industry profiles of workers. For example, to get earnings–based shares of college–educated workers in a particular industry, we sum the earnings of college–educated and non–college–educated workers in that industry and compute the ratio. We used this to compute, for each industry represented in the survey and for each year, the share of skilled worker earnings to total worker earnings, where "skilled" is defined by education level. Our base case cutoff for skilled workers is a college education (i.e. 16 years or higher), but we report other thresholds as well.

From the MP dataset we obtained 4–digit industry data on total factor productivity growth, factor payments to production and non–production workers, value added, employment, and stocks of capital equipment and structures annually over the period 1958–1991. In addition to providing the data on gross output–based TFP growth and capital stocks that we need to merge with the CPS data, we also consider a measure of skilled labor's share based on the earnings share of non–production workers. Finally, in computing labor's share in value added for each industry, we multplied the earnings in the MP data, which do not include fringe benefits and other non–wage compensation, by the corresponding 2–digit industry ratio of total compensation to wages for each year as computed from National Income and Product Accounts data.

There are two difficulties in merging the two data sources. The first is that the industry classifications in the CPS do not line up with the standard SIC numbers. There are CPS industries that include more than one SIC industry and vice–versa. As a consequence, for the work that involves merging the two data sets it was necessary to construct the "finest common coarsening" of industry classifications. After eliminating industries in which data are not available for the entire 1979–91 period, we were left with 67 industries. These were mainly three–digit level industries but there were several two– and four–digit industries as well, the latter notably including SIC 3573, "Electronic Computing Equipment." Table 1 provides the breakdown of these 67 industries in detail.

The second difficulty is that one cannot aggregate gross output, or gross output–based TFP without a great deal more information about input–output flows between 4–digit industries. Consequently for the merged data we construct value added–based TFP (see the appendix), so the factor shares for that portion of the empirical work are shares of value added rather than gross output.

To construct equipment's share we first obtain capital's share as a residual from labor's share (or from labor's and material's share of gross output). We then multiply that by

$$(r+\delta_{it}^{e})K_{it}^{e}Q_{t}^{e}/[(r+\delta_{it}^{e})K_{it}^{e}Q_{t}^{e}+(r+\delta_{it}^{p})K_{it}^{p}Q_{t}^{p})]$$

for industry i in year t, where we set r to be a constant (again, the results are not sensitive to specifications of variables that vary only over time). For the depreciation rates, we have obtained 4–digit depreciation rates for equipment and capital from Wayne Gray. Unfortunately, capital prices are not available at the 4–digit level, so we obtained 2–digit level prices of structures and equipment from the Commerce Department's *Fixed Reproducible Tangible Wealth* yearly, and applied them to the corresponding 4–digit industries.

Researchers have commonly used the production worker/non–production worker distinction as a proxy for unskilled versus skilled labor (e.g. Berman, Bound, and Griliches, 1994, Klenow, 1996, Kremer and Maskin, 1995)). This definition could actually be better than the education–based one, since it incorporates skills based on unobservables. On the other hand, the category does include some unskilled workers, and if the extent of this varied systematically with our explanatory variables there could be a problem. Moreover, the non–production worker definition arguably does not control for human capital as well as the education–based definitions. For the merged data set we are able to examine the correlation between this proxy and the education level. Since we find a fairly high correlation and similar econometric results, we then proceed to use the MP data exclusively. This dataset has the advantages of greater disaggregation (450 4–digit industries) and a longer time period.

3.2. Estimation

The focus of the paper will be on the patterns of growth in H^s. To that end, we will first proceed under the assumption that capital equipment is already measured accurately in efficiency units, and that there is no growth in unskilled labor's efficiency, so that $E_t = H_t^u = X_t = 1\ \forall t$. This is just to establish a simple benchmark case, which we will generalize in various directions to see how the initial results hold up. We rewrite (2.6) as

$$\Delta \ln TFP_{it} = \Delta \ln A_t + \alpha_{it}^s \Delta \ln H_t^s + \epsilon_{it} \tag{3.1}$$

Here ϵ_{it} has the interpetation of an idiosyncratic Hicks–neutral technology shock, while $\Delta \ln A_t$ (no industry subscript) is an aggregate Hicks–neutral change. If (within a given time period) skilled labor's share α_{it}^s is uncorrelated with ϵ_{it}, then a period–by–period regression of TFP growth on α_{it}^s will yield estimates of $\Delta \ln H_t^s$ and $\Delta \ln A_t$ for each t. (This of course would be equivalent to a pooled time series–cross section regression in which both the intercept and the $\{\alpha_{it}^s\}$ are interacted with time dummies.) Thus $\Delta \ln A_t$ has the interpretation of the increase in TFP in year t for the hypothetical industry with zero skilled labor share. Note that by assuming that ϵ_{it} is uncorrelated with α_{it}^s, we are essentially labeling as "skilled labor–augmenting" any growth in TFP that is systematically related in the data to skilled labor's share. Later we will control for equipment's share as well.

Our strategy will be to use the annual regression results as a guide to direct us toward patterns or trends in the data, as opposed to interpreting them literally as estimates of these effects. After presenting various results based on these regressions, we will use them to indicate a break point in the sample (which conveniently will fall near the middle for the 1958–91 data set). We will then rely more on lower frequency results based on industry averages over the subperiods to draw more conclusive results.

For skilled labor's share we first computed total labor share for each industry yearly from the ratio of wage payments to workers to value added, multiplied by the 2–digit level ratio of total compensation to wage payments from the NIPA as described earlier, and computed each industry's time average. We then multiplied that by the ratio of skilled wages to unskilled wages for each year. Thus we assume that total labor's share varies across industries but is constant over time (though the results were not sensitive to this assumption), whereas skilled labor's share varies across industries and time. There is in fact considerable growth over time in our measures of skilled labor's share.

3.3. Results

We first present results from 1979–1991 annual regressions on the merged data set, using the education level of 16 years or more as the cutoff for "skilled labor." The results we present are Weighted Least Squares estimates using industry employment as the weight. There are two reasons to weight by some measure of industry size. First, it is natural to give more weight to larger industries, since in effect they represent sums of smaller industries. Moreover, to some extent this is a history paper, and we want to know what happened in the economy, which argues for giving more weight to larger industries. The second reason is that there appears to be heteroscedasticity in the data, with the residual variance inversely related to size, as one might expect if the smallest industries have more noise in their data.

The regression results are provided in Table 2 for six different specifications. The first two columns give the "base case" specification: Skilled workers are defined as those with 16 or more years of schooling. The column labeled $\Delta \ln H^s$ provides the coefficients on skilled labor's share α^s_{it}, while the column labeled $\Delta \ln A$ has the coefficients on the constant and 12 year dummies. So the results say, for example, that an industry with a skilled labor share of 0.03 would have on average seen its TFP increase by a factor of $-0.017 + 0.03 \cdot 1.428 = .026$ or about 2.6 percent in 1979. An industry with a 0.01 share of skilled labor would have seen a *decline* in TFP growth of about 0.3 percent.

Since the regression results are a lot to absorb, we also provide some time plots related to the estimated coefficients. The top panel of Figure 1 is the corresponding time plot of the estimates of H and A. The lower panel is a plot of the contribution of H^s to total TFP. This was computed by multiplying the estimated growth in H for each year by that year's mean of α^s_t and accumulating over time with total TFP represented by adding to the contribution of H^s the estimated growth in A.

The main thing to notice is that there appears to be dramatic growth in H^s for the first two years of the sample, after which it levels off, while there is a decline in A over those same first years, after which it grows back roughly to where it began. The t–statistics from the regression show that the initial growth in H^s is statistically significant. Essentially, the regression results are saying that for the first few years of the sample, there was a significant association between TFP growth and skilled labor's share. The decline in A is attributable to the fact that the regression line fitted through the scatter of TFP growth and skilled labor's share has a negative intercept in those first few years—as if to say that an industry with zero or even just sufficiently low skilled labor's share would have experienced declines in TFP during those years.

The remainder of the results in Table 2 are for different specifications. The results were actually stronger using 14 years of schooling as the cutoff for the definition of "skilled," as well as for the definition of skilled as non–production workers. (The coefficients are smaller only because the average values of skilled labor's share under these alternative definitions are much larger). Note, however, that the results are considerably weaker for the 12–year cutoff. This is not surprising, since (see the discussion below) the evidence from wage data suggests that workers with no more than a high school education experienced a relative decline in wages since 1979. Table 3 shows the simple correlations of four different measures of skilled labor's share. The main thing to notice is that the share of non–production worker earnings is strongly correlated to the education–based measures. So the results are as robust as one would expect from the alternative definitions of skill.

At the same time, the relatively small number of industries makes the results somewhat sensitive to outliers. The last two columns of Table 2 provide results after alternately omitting the computer industry (SIC 3573) and newspaper printing and publishing (SIC 271). Eliminating the computer industry, which has very high TFP growth and a very high skilled labor share, weakens the results slightly. On the other hand, the newspaper industry experienced very low (in fact negative) TFP growth while also having a high share of skilled labor. The results are much stronger if this industry is left out. (Not reported in the table, if both industries are omitted, the results are comparable to the base case.)

While there may be grounds for suspecting the newspaper industry data (could it really have experienced a more than 45 percent decline in TFP over 13 years?)—especially considering that the industry has been beset by labor unrest—this sensitivity to outliers is of some concern. More importantly, it is unclear whether the jump in H that seemed to occur in the first two years of the sample is just an aberration, a statistical fluke, or part of something bigger. These considerations, plus the similarity of results using non–production workers' share, suggest that it would be reasonable to extend the same econometric exercise to the longer and more disaggregated dataset provided by the MP, using non–production workers as a proxy for skilled labor. For this we have, as mentioned earlier, gross output–based TFP, so the factor shares are relative to gross output.

The results of this exercise are depicted in Figure 2 and Table 4, using the non–production worker definition of skilled labor. These results buttress the findings from the shorter time period, but also put them in perspective. They indicate that the surge in skilled labor–augmenting technical progress was something of a historical aberration. There is essentially no growth in H^s until around 1973. It then grows dramatically from approximately between 1972 to 1981 (contributing a remarkable 1.81 percent annually to TFP growth for these ten years[3], or cumulatively over 18 percent), and then continues at a slower pace after that. Thus the relatively steady (albeit decelerating) growth of overall productivity (the solid line in the figure) conceals dramatic underlying shifts. Moreover, it turns out that although the outlier

[3]This comes from multiplying each year's estimate of $\Delta \log H$ by that year's average share of skilled labor in the sample, and then averaging over the values from 1974 through 1981.

industries mentioned above still exert a noticeable quantitative impact on the estimates, the results are qualitatively robust. For example, omitting industry 3573 reduces the size of the large positive coefficients by about 1/3, but they remain strongly significant. Eliminating the weighting by employment has similar effects. Omitting industry 2711 (newspaper printing and publishing) leads to stronger, but qualitatively similar results.[4]

In the same vein, Figure 3 provides weighted scatter diagrams of TFP growth and non–production worker shares for the years 1977–80, together with the regression line from Table 3 which support the view that the results are not driven by one or two outliers. The computer industry (SIC 3573, indicated in the figures) is an outlier in terms of TFP growth, but is close enough to the middle in its skilled labor share that it has only a slight influence on the regression results.

3.4. The Role of other Inputs

Clearly this mode of analysis can be extended to incorporate analogous effects through other inputs. We first relax the assumption that $E_t = 1 \; \forall t$ and estimate the equation

$$\Delta \ln TFP_{it} = \Delta \ln A_t + \alpha_{it}^s \Delta \ln H_t + \alpha_{it}^e \Delta \ln E_t + \epsilon_{it}. \tag{3.2}$$

This can be interpreted as allowing for mismeasurement of quality improvements in equipment, but does not distinguish between vintages of equipment. Thus if technical progress were only embodied in new equipment, and industry investment in new equipment were not proportional to its equipment factor intensity, then we would possibly miss some growth in E_t by using α_{it}^e. For example, suppose some technological development induces low α^e industries to undertake large purchases of new equipment that takes advantage of the new technology, but the new technology happens to be not

[4] We have also experimented with some corrections for serial correlation in the residuals, but the results were very similar.

particularly useful for high α^e industries. TFP growth would consequently occur only in the low α^e industries, and we could mistakenly obtain a negative estimate of $\Delta \ln E_t$.

We first add equipment's share to the regressions from the 1979–91 merged data set, with the education–based (16 years) measure of skilled labor. We use the NIPA deflator for manufacturing equipment in computing the share, though the results (which, after all, come from primarily from the cross–sectional variation of the share) are not sensitive to this. These results are reported in Table 5. They show little evidence of a substantial role for equipment effects, while the skilled labor effects are quite similar to those from Table 2. The results were similar when capital's share was used instead of equipment's share.

Results for the 1958–91 period using the non–production worker definition were similarly inconclusive regarding equipment or capital effects, but the skilled labor effects are still significant. Figure 4 depicts the estimated H^s and E series along with TFP for the specification in which E multiplies total capital. Similar results were obtained with using equipment rather than total capital. The effects of H^s between 1973 and 1981 are strongly significant. Note that this figure depicts the effects in terms of their contributions to TFP (as in the bottom panels of Figures 1 and 2). Thus we estimate an approximate 20 percent increase in TFP through growth in H^s during this eight–year period. The decline in E after 1973 looks a little strange, but only the drop in the last four years is significant. It is also somewhat sensitive to outliers and specification. In general, although none of the various specifications finds any substantial growth in E, no other clear pattern emerges, whereas the finding of this 1973–81 growth spurt in H^s is a common feature of all specifications except in some cases where industries are not weighted by size. One interpretation of this could be that although capital improves in quality, the increase in TFP fails to emerge unless skilled labor is present.

Another pattern in Figure 4 that is also present in Figure 2 is the drop in H^s in the few years prior to 1973. Greenwood and Yorukoglu (1996) and Hornstein and Krusell (1996) have argued that increases in technical change could result in lower TFP growth. The argument is that the introduction of substantially new technologies can reduce measured productivity in the short run as workers adapt and learn new techniques. Indeed, Greenwood–Yorukoglu argue on the basis of aggregate evidence that precisely this was going on in the early 1970s.

3.5. Embodied Technical Progress

Most stories about skill–biased technical change center around plant retooling or expansion. Dunne, Haltiwanger, and Troske (1996), for example, provide evidence that changes in non–production workers' share in plant level data are associated with changes in the scale of operation of the plants. We therefore also consider a specification that is designed to capture technical progress that is embodied only in new capital. In deriving this specification we will lump plant and equipment together into total capital K (that is, $K = K^p + K^e$). We can and will do the same exercise separately for equipment, using industry–specific depreciation rates for equipment and structures to impute separate series for investment in each type of capital.

Suppose we call $K_t^* \equiv K_t E_t$, where K^* is the capital stock measured in efficiency units. Suppose further that

$$K_t^* = K_{t-1}^*(1-\delta) + I_{t-1}Z_{t-1} \tag{3.3}$$

where Z_t measures investment goods in efficiency units, while I_t is the measured quantity of investment (i.e. $K_{t+1} - (1-\delta)K_t$). Now $\Delta \ln E_t = \Delta \ln K_t^* - \Delta \ln K_t$ by definition. And we have

$$\Delta \ln K_t \quad = \quad -\delta + I_{t-1}/K_{t-1}$$

$$\Delta \ln K_t^* \;=\; -\delta + I_{t-1}Z_{t-1}/K_{t-1}^* = -\delta + \frac{I_{t-1}Z_{t-1}}{K_{t-1}E_{t-1}}.$$

Hence $\Delta \ln E_t = (I_{t-1}/K_{t-1})(Z_{t-1}/E_{t-1} - 1)$. Consequently, an alternative specification of (3.2) would be

$$\Delta \ln TFP_{it} = \Delta \ln A_t + \alpha_{it}^s \Delta \ln H_t + \alpha_{it}^k (I_{it-1}/K_{it-1})(Z_{t-1}/E_{t-1} - 1) + \epsilon_{it}. \qquad (3.4)$$

where α^k is capital's share. (Note that from (3.3) we have $K_t^* = \sum_{\tau=1}^{\infty}(1-\delta)^{\tau} I_{t-\tau} Z_{t-\tau}$, which implies that

$$E_t = \frac{\sum_{\tau=1}^{\infty}(1-\delta)^{\tau} I_{t-\tau} Z_{t-\tau}}{\sum_{\tau=1}^{\infty}(1-\delta)^{\tau} I_{t-\tau}}$$

which is a weighted average of current and lagged Zs and hence will always be smaller than Z_t if Z monotonically increases over time.) Thus one could in principle estimate the same type of equation but replacing α_{it}^e with $\alpha_{it}^k (I_{it-1}/K_{it-1})$ on the right–hand side. Of course in general one would expect I_{it-1}/K_{it-1} to be correlated with ϵ_{it}, so it would be necessary to use instrumental variables. We can use factor shares (which we have assumed to be uncorrelated with the residual) as instruments for $\alpha_{it}^k (I_{it}/K_{it})$. It will turn out, however, that estimation of (3.4) will yield very similar results to those of (3.2). Thus there is little evidence that the embodied/disembodied distinction is very important for this purpose.

The same pattern in H^s effects persists in results incorporating embodied progress in overall capital or in equipment. Figure 5 depicts the contributions to TFP based on the regression $\Delta \ln TFP_{it} = \Delta \ln A_t + \alpha_{it}^s \Delta \ln H_t^s + \alpha_{it}^e (I_{it-1}^e / K_{it-1}^e) \Delta \ln E_t + \epsilon_{it}$, using α_{it}^e, α_{it-1}^e, α_{it-1}^s, and α_{it}^k as instruments. Note that the pattern in E's contribution to TFP is different from that depicted in Figure 4 (though it still exhibits a downard trend), whereas the contribution of H^s is very similar.

Finally, the specification of technology (2.1) or (2.2) permits other analogous effects as well. Tables 6 and 6a gives some representative results from more general specifications (for the cases of disembodied and embodied technical improvements in capital), just to show that the H^s effects are robust. These are based on lumping structures and equipment together, but similar results were found treating equipment separately (and assuming technical progress is embodied only in equipment). The only other striking pattern to emerge is the persistent negative H^u effects. This could represent actual diminished quality of unskilled labor during this period, but this probably deserves more scrutiny.

To summarize these results: We find robust evidence of a surge in skilled labor–augmenting technical progress during the period from 1973 to 1981 (as measured by the extent to which TFP growth is associated with skilled labor's share across industries), even after controlling for other factors such as new investment, human capital (to the extent possible), and outlier industries such as the computer industry. Somewhat surprisingly, we fail to find evidence that capital—total plant and equipment, just equipment, or just new plant and/or equipment—plays a significant role. We will next consider related evidence based on lower frequency data (i.e. time averages of the panel data considered above, broken into pre– and post–1973 subperiods), along with independent evidence based on aggregate time series.

3.6. Low Frequency Implications and Evidence

It is worth pointing out that the presence of skilled labor–augmenting technical progress is not immediately apparent in the MP data.[5] As Klenow (1996) points out (in a study that uses essentially the same MP data as this study), there is no correlation between average industry TFP growth and skilled labor's share. How can this be so? Even though the results suggest that this phenomenon was to some extent a historical aberration, it should still be evident in a cross–section study such as

[5] Table 3 suggests that there is in the merged data set, but in fact the positive correlations with TFP are sensitive to the treatment of outliers.

Klenow's if the data include that period, since although skilled labor's share varies, the high–skill industries tend to be the same over time. It turns out that there are two explanations. First, as mentioned earlier, our results not as strong without the weighting by industry size. The data from small industries appear to be noisier, so a simple cross–sectional correlation that fails to take this into account will tend toward zero. Second, controlling for equipment's share actually increases the correlation between skilled labor's share and TFP growth. (Rather surprisingly, equipment's share and non–production workers' share are negatively correlated in the cross–section.)

To document this we next provide results based on a cross section of industry averages. Table 7 provides regression results based on (3.2) modified to include equipment effects, i.e.:

$$\hat{TFP}_i = \hat{A}_i + \bar{\alpha}_i^s H + \bar{\alpha}_i^e E + \epsilon_i \tag{3.5}$$

from the cross–section of 450 industry averages over 1959–73 and 1974–91 subsamples, where the "^" refers to the average growth rate of the underlying variable, and the "–" over the shares indicate industry averages over the same period. Both OLS and WLS results are provided, with and without equipment's share. The unweighted regression without equipment's share reproduces Klenow's negative result, but the others show that both weighting by industry size and controlling for equipment's share increases the estimated effect of skilled labor's share. The WLS estimates of $\hat{H}$ for the 1974–91 period range from 0.059 to 0.197, which correspond to a range of contributions to TFP of 0.70 percent up to 2.3 percent annually (the weighted average share of non–production workers in gross output is 0.119), compared to a weighted average overall TFP growth rate in the sample of 0.80 percent. Again the estimates of $\hat{E}$ appear to be sensitive to the specification, while there are again persistent negative effects from production–workers share. But the main thing to notice is the clear difference between the two subsamples with regard to the estimates of $\hat{H}^s$.

3.7. Aggregate Time Series Evidence

It turns out that with a little more structure on technology we can get evidence on the average growth rates of H^s, E, and A from the joint behavior of the growth rates of outputs, inputs and factor prices in aggregate data. Suppose the production function for industry i is CES:

$$y_{it} = A_{it}[\alpha_i^p K_{it}^{p^{1-\theta}} + \alpha_i^e (K_{it}^e E_t)^{1-\theta} + \alpha_i^s (H_t N_{it}^s)^{1-\theta} + \alpha_i^u N_{it}^{u^{1-\theta}}]^{\frac{1}{1-\theta}}, \tag{3.6}$$

where $\Sigma_k \alpha_i^k = 1$ and $\theta > 0$. Note that industries may differ in the share parameters α_i^k, but they are assumed to have the substitution elasticity parameter θ. From the first–order conditions we have

$$\begin{aligned} \hat{P}_i + \theta(\hat{y}_i - \hat{K}_i^p) + (1-\theta)\hat{A} &= \hat{Q}^p, \\ \hat{P}_i + \theta(\hat{y}_i - \hat{K}_i^e) + (1-\theta)(\hat{A} + \hat{E}) &= \hat{Q}^e, \\ \hat{P}_i + \theta(\hat{y}_i - \hat{N}_i^s) + (1-\theta)(\hat{A} + \hat{H}^s) &= \hat{W}^s + \hat{H}^s \\ \hat{P}_i + \theta(\hat{y}_i - \hat{N}_i^u) + (1-\theta)\hat{A} &= \hat{W}^u. \end{aligned} \tag{3.7}$$

Cobb–Douglas production is the special case in which $\theta = 1$. In that case we obviously cannot learn anything about $\hat{E}$ and $\hat{H}^s$ from aggregate data. But otherwise we can look at the aggregate average growth rates of these variables and solve for $\hat{A}$, $\hat{H}^s$, $\hat{E}$, and θ. We do this using two different (though overlapping) data sources. First we use the data from the MP database, which include value added, the capital stocks, and earnings for production and non–production workers (modified as before to factor in non–wage compensation). To this we add the NIPA deflators for manufacturing equipment and structures, and the producer price index. Also, because there is a general consensus that quality changes in equipment have been poorly captured by the NIPA measures (see Gordon, 1990, Greenwood, Hercowitz, and Krusell, 1995), we also consider an adjustment to $\hat{K}^e$ based on Gordon's (1990) price index.

The second data set is entirely from the NIPA: We use aggregate manufacturing output, production worker earnings (computed from employment, weekly hours, and hourly earnings), total labor compensation, total labor wage and salary payments, total employment (from which we subtract production worker employment to get non–production worker employment). We impute a compensation rate for both types of workers, under the assumption that the ratio of total compensation to wage and salary payments is the same. It probably is not, but this is not so important for working with growth rates. We do want to capture the extra growth in labor compensation that comes from growth in fringe benefits relative to wage and salaries. We would only be off in this calculation if fringe benefits relative to wages grew by more for one type of worker than the other.

We compute $\hat{A}$, $\hat{H}^s$, $\hat{E}$, and θ for the 1959–91 period, and also separately for the 1959–73 and 1974–91 periods, for each of the two datasets. We want to see whether the "regime shift" evident from the disaggregated data—that in the earlier period $\hat{H}^s$ was if anything negative, while in the second it is strongly positive—also shows up in aggregate behavior.

The results are given in Table 8. Regarding $\hat{H}^s$ they are remarkably consistent with the findings from the disaggregated data, considering that they are based on an entirely different computation. These results make no use of cross–sectional variation or of factor shares, but are based entirely on the joint behavior of aggregate average growth rates of inputs, outputs, and factor prices. For example, $\hat{H}^s$ is measured from the growth of N^s/N^u relative to the growth of the relative wage W^sH^s/W^u. The estimate is higher in the later period because the growth in the relative inputs increased relative to the growth in relative wages. Though obviously there are no standard errors to this exercise, both datasets show a clear regime shift pre– and post–1973 era. Just taking the average of the two estimates, $\hat{A}$ goes from 1.876 to -0.205 percent, while $\hat{H}^s$ goes from -0.076 to 1.70 percent, and $\hat{E}$ goes from -1.474 to 2.469 percent (or from -0.194 to 5.195 percent by the alternative measure). The estimates of θ range from approximately 0.1–0.4, which represents a relatively high degree of substitutability between factors. While this is a wide range, and the estimates do not seem especially stable across the different time periods, the qualitative results are not very sensitive to the choice of θ. [6]

The only inconsistency between these findings and the cross–section findings is the evidence of growth in E as well as in H^s. But this is consistent with the Table 7 cross–section regressions, and provides further confirmation of significant equipment effects only in low frequency data. Thus the behavior of the growth rates of inputs, output, and prices in aggregate manufacturing strikingly confirm the evidence from disaggregated data that beginning in around 1972 technical progress began to be more selective in its impact, increasing the relative productivity of skilled workers and the efficiency of equipment, and consequently increasing the productivity of industries relatively intensive in those factors.

3.8. Patterns in Wage Rates and Employment

Katz and Murphy (1992) document large increases in the relative wages of more educated workers, particularly those with relatively low experience, over the period from 1963 to 1987. For those with one to five years of experience, wages of college–educated workers rose by 12.2 percent relative to high–school dropouts. Breaking down this time period into shorter intervals, they note that between 1963 and 1971 the relative wages stayed fairly even. From 1971–1979 the college education premium actually declined (by 12.8 percent for the low experience group), a fact they attribute to a large supply increase. But from 1979–1987 the premium jumped dramatically, by 26.6 percent for the low experience group. Over this same period the

[6] To get a sense of the contribution of H and E in the later period, note that average production worker's share in the ASM data from 1974 to 1991 is 0.217, while equipment's average share is 0.258. Hence the contributions would be 0.28 and 0.97 percent respectively. The corresponding calculation for the NIPA data are .85 and .22 percent for $\hat{H}$ and $\hat{E}$ respectively. Both estimates of $\hat{E}$ would of course be larger with the Gordon–based measure of $\hat{K}^e$.

premium of college over high school–educated actually rose by 30.6 percent.[7]

Murphy and Welch (1992) also document this phenomenon of "skill–biased technical change," and their time breakdowns correspond more closely to the periods highlighted in our analysis. They show that the hourly wages of college graduates relative to high school graduates was 1.52 in 1969, 1.39 in 1974, 1.30 in 1979, 1.63 in 1984, and 1.74 in 1989 for workers with one to five years of experience. Thus in the five years from 1979 to 1984 the premium rose by over 25 percent. Again, the large increase in young college educated workers in the 1969–79 period (presumably due in part to the baby boom and in part to the incentives spawned by the Vietnam War) could have swamped any increase in demand for them. But the overall increase in this premium of 17.3 percent from 1974–1984 in spite of the large increases in supply suggests that there was a substantial increase in the relative demand for educated workers.

Other work in this area focuses on employment patterns. Berman, Bound, and Griliches (1994) document a sustained increase in the share of non–production workers in the wage bill of U.S. manufacturing during the period from 1959–89, with an acceleration after 1979. They also show that much of this increase occured within industries, and therefore does not represent the effect of shifts in product demands. Dunn, Haltiwanger, and Troske (1996) carry this last point one step further and show that the bulk of the increases in non–production workers' share is within plants. They conclude that "individual plants have fundamentally changed the way they produce goods in terms of the mix of workers. . . ."

Although the model presented earlier does not have any automatic implications for patterns of relative wage rates and employment of skilled and unskilled workers, from the system 3.7 we can illuminate the relationship between skilled labor–augmenting technical progress and skill–biased technical change. From the

[7] Katz and Murphy also document dramatic increases in relative wages of more experienced workers within the lower education groups. Our schooling–based measure of skilled labor's share overlooks the contribution of experience as a substitute for schooling.

equations for skilled and unskilled labor we have

$$\hat{N}_i^s - \hat{N}_i^u = \frac{(1-\theta)}{\theta}\hat{H}^s - \frac{1}{\theta}(\hat{W}^s + \hat{H}^s - \hat{W}^u)$$

for within–industry changes in relative labor demand. In terms of the change in skilled labor's share, we get

$$\hat{N}_i^s - \hat{N}_i^u + (\hat{W}^s + \hat{H}^s - \hat{W}^u) == \frac{(1-\theta)}{\theta}\left[\hat{W}^u - \hat{W}^s\right].$$

The term $\hat{W}^u - \hat{W}^s$ would be positive except in the extreme case that the equilibrium skill premium increases one–for–one with H^s. Thus growth in $\hat{H}^s$ corresponds to skill–biased technical change only to the extent that $\theta < 1$, i.e. that the elasticity of substitution across factors is greater than one. So growth in H^s is certainly capable of causing growth in the skill premium, and the small values for θ found in Table 8 are consistent with this explanation.

To summarize: Provided the elasticity of substitution is sufficiently greater than one, our finding that H^s grew substantially (and without precedent) during the period 1973–1982 is broadly consistent with the the above–referenced literature's finding of skill–biased technical progress, though the acceleration in H^s may precede somewhat the acceleration of the growth in non–production workers' share. The patterns in the skilled wage premium also and match up well with the regression results that indicate skilled labor–related growth in TFP during the roughly the same time period of approximately 25 percent.

Regarding the precise timing of these various shifts: the fact that the TFP effects appear to have preceded the acceleration in skilled labor's share documented by Berman et al. would suggest a story in which skilled labor–augmenting technical progress does not immediately translate into increases in skilled labor's share, but does so with a lag. This could result from long–term labor contracts, the need to retool plants, or other types of adjustment costs.

4. Conclusions

This paper has provided a variety of evidence of major sectoral shifts in productivity growth during the 1970s and 80s. It documents a surge in productivity growth favoring industries with high shares of skilled labor that began around 1973 and continued for at least eight to ten years. The effects are present even after controlling for analogous capital equipment effects. These findings complement earlier studies of wage and employment patterns that find that the demand for skilled workers rose sharply beginning in the early seventies: Provided the elasticity of substitution across factors is greater than one, our interpretation of these patterns in TFP growth as skilled labor–augmenting technical progress is consistent with—and arguably accounts for—skill–biased technical progress. The more recent evidence suggests that the pace of skilled labor– and equipment–augmenting technical progress has slowed, which would suggest a settling of the distribution of income.

The timing of the surge in skilled labor–augmenting technical progress also coincides with Greenwood and Yorukoglu's timing of the "watershed" that they argue initiated both the rise in income inequality and the slowdown of aggregate productivity. They provide evidence of large increases in the rate of investment in "information technology" (along with steep price declines in new equipment). They provide a story for why the surge occurred: An acceleration of technical progress in information technology (manifesting itself in lower equipment prices). They suggest that the new technology requires investment in learning–a task performed only by skilled workers–which causes measured productivity to fall initially. We would embellish that story with the feature that industries with larger shares of skilled labor can more quickly absorb the new technology and translate it into higher productivity (in their model industries do not differ in that dimension).

Table 1: SIC Industry Codes for Merged Dataset

Ind.	SIC Codes	Ind.	SIC Codes	Ind.	SIC Codes
1	201	24	281, 286, 289	47	346
2	202	25	282	48	351
3	203	26	283	49	352
4	205	27	284	50	353
5	206, 207, 209	28	285	51	354
6	208	29	287	52	355, 356, 358, 359
7	210	30	291	53	3574, 3576, 3579
8	221–224, 228	31	295, 299	54	3573
9	225	32	301	55	361, 362, 364, 367, 369
10	226	33	302–304, 306	56	363
11	227	34	307	57	365, 366
12	229	35	311	58	371
13	231–237	36	312–317, 319	59	372
14	239	37	321, 322, 323	60	373
15	241	38	324, 327	61	374
16	242, 243	39	325	62	375, 376, 379
17	244, 249	40	326	63	381, 382
18	25	41	328, 329	64	383–385
19	261–263, 266	42	33	65	386
20	264	43	341, 343, 347–349	66	387
21	265	44	342	67	39
22	271	45	344		
23	272–279	46	345		

Table 2: Regression Results, Merged Dataset

	Skill Definition					
	16 years		14 years		12 years	
Year	$\Delta logH$	$\Delta logA$	$\Delta logH$	$\Delta logA$	$\Delta logH$	$\Delta logA$
const		-0.022		-0.052		-0.071
		(0.017)		(0.024)		(0.054)
79	1.428	0.005	0.825	0.014	0.113	0.037
	(0.776)	(0.022)	(0.312)	(0.030)	(0.111)	(0.068)
80	3.636	-0.078	1.237	-0.052	0.132	-0.008
	(0.747)	(0.023)	(0.278)	(0.030)	(0.111)	(0.068)
81	0.601	0.010	0.090	0.046	-0.159	0.130
	(0.680)	(0.023)	(0.325)	(0.032)	(0.116)	(0.070)
82	-0.051	0.004	-0.464	0.063	-0.394	0.200
	(0.612)	(0.023)	(0.273)	(0.031)	(0.117)	(0.070)
83	0.786	0.032	0.594	0.041	0.063	0.076
	(0.563)	(0.023)	(0.266)	(0.031)	(0.119)	(0.071)
84	-0.168	0.073	-0.020	0.100	-0.079	0.149
	(0.529)	(0.022)	(0.274)	(0.031)	(0.123)	(0.073)
85	0.829	0.005	0.465	0.021	0.094	0.040
	(0.515)	(0.024)	(0.244)	(0.032)	(0.123)	(0.074)
86	-0.064	0.025	0.017	0.052	-0.082	0.106
	(0.567)	(0.025)	(0.235)	(0.032)	(0.127)	(0.075)
87	-0.657	0.115	-0.224	0.144	-0.223	0.235
	(0.464)	(0.023)	(0.236)	(0.032)	(0.124)	(0.075)
88	-0.982	0.072	-0.172	0.087	0.081	0.059
	(0.464)	(0.023)	(0.248)	(0.032)	(0.121)	(0.074)
89	-0.498	0.031	-0.065	0.052	-0.012	0.070
	(0.439)	(0.023)	(0.222)	(0.032)	(0.121)	(0.075)
90	0.615	0.001	0.315	0.022	0.059	0.044
	(0.433)	(0.023)	(0.216)	(0.032)	(0.122)	(0.075)
91	0.219		0.389		0.134	
	(0.427)		(0.232)		(0.127)	
	$R^2 = 0.187$		$R^2 = 0.189$		$R^2 = 0.168$	

Table 2 (cont.): Regression Results, Merged Dataset

	Non–prod. workers		Omitting 3573		Omitting 271	
Year	$\Delta logH$	$\Delta logA$	$\Delta logH$	$\Delta logA$	$\Delta logH$	$\Delta logA$
const.		-0.049		-0.017		-0.043
		(0.029)		(0.014)		(0.019)
79	0.388	-0.013	0.561	0.011	2.978	0.004
	(0.141)	(0.039)	(0.644)	(0.018)	(1.032)	(0.026)
80	0.705	-0.116	2.182	-0.062	4.141	-0.065
	(0.138)	(0.040)	(0.626)	(0.019)	(0.792)	(0.025)
81	0.096	0.030	-0.467	0.021	0.806	0.028
	(0.136)	(0.040)	(0.576)	(0.019)	(0.754)	(0.025)
82	-0.173	0.065	-0.656	0.009	0.085	0.023
	(0.138)	(0.041)	(0.530)	(0.019)	(0.709)	(0.025)
83	-0.118	0.102	0.020	0.039	1.120	0.047
	(0.133)	(0.041)	(0.468)	(0.019)	(0.607)	(0.025)
84	-0.077	0.112	-1.320	0.087	0.013	0.090
	(0.129)	(0.040)	(0.450)	(0.018)	(0.613)	(0.025)
85	0.183	0.017	0.053	0.016	1.283	0.015
	(0.126)	(0.040)	(0.435)	(0.020)	(0.568)	(0.026)
86	0.024	0.045	-0.577	0.029	0.024	0.044
	(0.125)	(0.041)	(0.467)	(0.020)	(0.644)	(0.027)
87	-0.115	0.147	-1.096	0.118	-0.508	0.133
	(0.121)	(0.040)	(0.382)	(0.019)	(0.492)	(0.025)
88	-0.174	0.107	-0.953	0.066	-0.867	0.090
	(0.119)	(0.040)	(0.388)	(0.019)	(0.530)	(0.025)
89	-0.132	0.072	-0.660	0.029	-0.405	0.050
	(0.118)	(0.040)	(0.361)	(0.019)	(0.473)	(0.025)
90	0.247	-0.007	0.414	-0.000	1.197	0.007
	(0.119)	(0.040)	(0.357)	(0.019)	(0.479)	(0.025)
91	0.156		0.012		0.948	
	(0.126)		(0.357)		(0.517)	
	$R^2 = 0.193$		$R^2 = 0.244$		$R^2 = 0.205$	

Table 3: Sample Statistics on Measures of Skilled Labor Share and TFP Growth

	$\alpha(16)$	$\alpha(14)$	$\alpha(12)$	$\alpha(NP)$	ΔTFP(%)
Sample Mean	0.024	0.071	0.376	0.197	1.211
Corr. with $\alpha(16)$	1.000	0.959	0.839	0.919	0.236
Corr. with TFP	0.182	0.208	0.120	0.174	1.000

$\alpha(n)$ = skilled worker share based on n yrs. of schooling, or on non–production workers (NP). Statistics are employment–weighted.

Table 4: Regression Results with MP Dataset, 1959–91

Year	ΔlnH	ΔlnA	Year	ΔlnH	ΔlnA
c.		-0.017	75	0.160	-0.041
		(0.004)		(0.035)	(0.006)
59	-0.261	0.074	76	-0.033	0.048
	(0.040)	(0.006)		(0.034)	(0.006)
60	-0.019	0.011	77	0.172	0.021
	(0.038)	(0.006)		(0.032)	(0.006)
61	0.103	0.010	78	0.106	0.016
	(0.036)	(0.006)		(0.031)	(0.006)
62	-0.022	0.047	79	0.259	-0.004
	(0.035)	(0.006)		(0.029)	(0.006)
63	0.062	0.037	80	0.422	-0.037
	(0.034)	(0.006)		(0.029)	(0.006)
64	-0.033	0.037	81	0.123	0.004
	(0.035)	(0.006)		(0.029)	(0.006)
65	-0.024	0.044	82	-0.014	0.010
	(0.033)	(0.006)		(0.029)	(0.006)
66	0.086	0.010	83	-0.045	0.044
	(0.032)	(0.006)		(0.028)	(0.006)
67	0.062	0.011	84	-0.043	0.047
	(0.030)	(0.006)		(0.026)	(0.006)
68	-0.052	0.041	85	0.031	0.025
	(0.029)	(0.006)		(0.026)	(0.006)
69	0.073	0.011	86	0.037	0.013
	(0.029)	(0.006)		(0.025)	(0.006)
70	-0.090	0.001	87	0.018	0.053
	(0.031)	(0.006)		(0.025)	(0.006)
71	-0.262	0.063	88	-0.116	0.034
	(0.034)	(0.006)		(0.024)	(0.006)
72	0.144	0.020	89	-0.077	0.024
	(0.035)	(0.006)		(0.024)	(0.006)
73	-0.025	0.050	90	-0.018	0.016
	(0.034)	(0.006)		(0.024)	(0.006)
74	0.230	-0.013	91	0.053	
	(0.034)	(0.006)		(0.026)	

$R^2 = 0.170$

Table 5: Regression Results with Equipment Share, Merged Dataset

Year	ΔlnA	ΔlnH^s	ΔlnE
79	0.0140	1.3761	-0.0944
	(0.0423)	(0.7760)	(0.1219)
80	0.0119	3.2534	-0.3289
	(0.0459)	(0.7570)	(0.1264)
81	-0.0153	0.6071	0.0096
	(0.0444)	(0.6788)	(0.1251)
82	-0.1093	-0.0380	0.2781
	(0.0450)	(0.6089)	(0.1290)
83	-0.0489	0.7646	0.1820
	(0.0452)	(0.5604)	(0.1306)
84	0.0033	-0.1658	0.1442
	(0.0443)	(0.5262)	(0.1265)
85	0.0342	0.7801	-0.1507
	(0.0468)	(0.5139)	(0.1280)
86	0.0508	-0.0712	-0.1410
	(0.0470)	(0.5639)	(0.1290)
87	0.0492	-0.6537	0.1285
	(0.0442)	(0.4613)	(0.1218)
88	-0.0140	-0.9775	0.1876
	(0.0435)	(0.4611)	(0.1193)
89	-0.0181	-0.5313	0.0828
	(0.0418)	(0.4397)	(0.1180)
90	0.0120	0.6280	-0.0976
	(0.0429)	(0.4304)	(0.1162)
91	0.0172	0.2093	-0.1113
	(0.0453)	(0.4255)	(0.1190)

$R^2 = 0.2096$

Table 6: Regression Results with Total Capital, Disembodied Capital Improvement

$$\Delta lnTFP_{it} = \Delta lnA_t + \alpha^s_{it}\Delta lnH^s_t + \alpha^u_{it}\Delta lnH^u_t + \alpha^k_{it}\Delta lnE_t$$

Year	ΔlnA	ΔlnH^s	ΔlnH^u	ΔlnE	Year	ΔlnA	ΔlnH^s	ΔlnH^u	ΔlnE
59	0.0253	-0.3362	0.0437	0.1497	76	0.0770	0.0006	-0.2058	-0.0576
	(0.0122)	(0.0554)	(0.0451)	(0.0493)		(0.0096)	(0.0339)	(0.0343)	(0.0317)
60	0.0143	0.0042	-0.1036	-0.0186	77	0.0125	0.1726	-0.0556	0.0024
	(0.0096)	(0.0430)	(0.0359)	(0.0389)		(0.0098)	(0.0332)	(0.0351)	(0.0318)
61	-0.0091	0.1073	0.0237	-0.0154	78	0.0314	0.1299	-0.1418	-0.0431
	(0.0072)	(0.0285)	(0.0270)	(0.0281)		(0.0105)	(0.0345)	(0.0371)	(0.0342)
62	0.0440	-0.0012	-0.0397	-0.0443	79	0.0428	0.3252	-0.2169	-0.1510
	(0.0058)	(0.0228)	(0.0216)	(0.0227)		(0.0104)	(0.0335)	(0.0361)	(0.0342)
63	0.0334	0.0893	-0.0047	-0.0749	80	0.0321	0.5094	-0.2545	-0.2324
	(0.0088)	(0.0319)	(0.0327)	(0.0335)		(0.0146)	(0.0448)	(0.0493)	(0.0460)
64	0.0151	-0.0463	-0.0032	0.0307	81	0.0320	0.1278	-0.2037	-0.0457
	(0.0043)	(0.0167)	(0.0162)	(0.0166)		(0.0125)	(0.0371)	(0.0419)	(0.0394)
65	0.0261	-0.0332	-0.0185	0.0256	82	0.0074	-0.0365	-0.1171	0.0368
	(0.0053)	(0.0203)	(0.0197)	(0.0205)		(0.0123)	(0.0341)	(0.0408)	(0.0375)
66	-0.0069	0.0881	0.0016	-0.0064	83	0.1378	-0.0255	-0.4098	-0.1970
	(0.0047)	(0.0177)	(0.0174)	(0.0179)		(0.0135)	(0.0351)	(0.0453)	(0.0409)
67	-0.0399	0.0254	0.0968	0.0921	84	0.0607	-0.0758	-0.2135	0.0398
	(0.0079)	(0.0273)	(0.0286)	(0.0286)		(0.0152)	(0.0386)	(0.0507)	(0.0471)
68	0.0676	-0.0265	-0.1928	-0.0573	85	0.1104	0.0586	-0.3198	-0.2358
	(0.0075)	(0.0247)	(0.0272)	(0.0267)		(0.0128)	(0.0309)	(0.0425)	(0.0393)
69	-0.0024	0.0591	-0.0689	0.0480	86	0.0287	0.0218	-0.1660	-0.0146
	(0.0054)	(0.0179)	(0.0196)	(0.0190)		(0.0117)	(0.0270)	(0.0397)	(0.0350)
70	-0.0272	-0.1187	-0.0163	0.0818	87	0.0679	-0.0030	-0.1764	0.0019
	(0.0079)	(0.0271)	(0.0291)	(0.0271)		(0.0116)	(0.0265)	(0.0391)	(0.0345)
71	0.0636	-0.2659	-0.1440	0.0349	88	0.0425	-0.0796	0.0005	-0.1367
	(0.0079)	(0.0291)	(0.0300)	(0.0277)		(0.0107)	(0.0239)	(0.0356)	(0.0313)
72	-0.0460	0.0102	0.0035	0.2867	89	0.0333	-0.0659	-0.0617	-0.0802
	(0.0113)	(0.0424)	(0.0416)	(0.0387)		(0.0086)	(0.0190)	(0.0285)	(0.0248)
73	0.0599	0.0340	-0.0405	-0.1176	90	0.0503	0.0168	-0.0945	-0.1797
	(0.0100)	(0.0372)	(0.0364)	(0.0341)		(0.0102)	(0.0231)	(0.0343)	(0.0296)
74	0.0358	0.3052	-0.2547	-0.1272	91	0.0699	0.1161	-0.1646	-0.3015
	(0.0134)	(0.0499)	(0.0481)	(0.0452)		(0.0097)	(0.0225)	(0.0329)	(0.0284)
75	-0.0236	0.1843	-0.1682	-0.0320					
	(0.0141)	(0.0514)	(0.0508)	(0.0465)					

Table 6a: Regression Results, Embodied Capital Improvement

$$\Delta lnTFP_{it} = \Delta lnA_t + \alpha^s_{it}\Delta lnH^s_t + \alpha^u_{it}\Delta lnH^u_t + \alpha^k_{it}(I_{it-1}/K_{it-1})\Delta lnE_t$$

Year	ΔlnA	ΔlnH^s	ΔlnH^u	ΔlnE	Year	ΔlnA	ΔlnH^s	ΔlnH^u	ΔlnE
60	0.0267	0.0332	-0.0979	-1.2514	76	0.0704	-0.0192	-0.1926	-0.3938
	(0.0079)	(0.0382)	(0.0347)	(0.2777)		(0.0084)	(0.0311)	(0.0336)	(0.3474)
61	-0.0051	0.1191	0.0254	-0.6302	77	0.0116	0.1708	-0.0549	0.0811
	(0.0063)	(0.0275)	(0.0273)	(0.2515)		(0.0091)	(0.0322)	(0.0345)	(0.3466)
62	0.0397	-0.0092	-0.0399	-0.2829	78	0.0411	0.1477	-0.1507	-1.0510
	(0.0051)	(0.0223)	(0.0216)	(0.2227)		(0.0106)	(0.0350)	(0.0381)	(0.3981)
63	0.0384	0.1008	0.0117	-1.7158	79	0.0372	0.3570	-0.2004	-1.7139
	(0.0079)	(0.0311)	(0.0335)	(0.3634)		(0.0101)	(0.0397)	(0.0383)	(0.4001)
64	0.0220	-0.0301	-0.0032	-0.1398	80	0.0131	0.5961	-0.2436	-2.2205
	(0.0040)	(0.0155)	(0.0161)	(0.1752)		(0.0134)	(0.0598)	(0.0530)	(0.4974)
65	0.0280	-0.0270	-0.0210	0.1689	81	0.0527	0.2424	-0.2464	-1.8390
	(0.0048)	(0.0192)	(0.0199)	(0.1829)		(0.0116)	(0.0463)	(0.0449)	(0.3999)
66	-0.0039	0.0962	0.0051	-0.2680	82	0.0203	0.0045	-0.1377	-0.3297
	(0.0045)	(0.0179)	(0.0177)	(0.1793)		(0.0102)	(0.0472)	(0.0420)	(0.3808)
67	-0.0223	0.0602	0.0931	-0.0731	83	0.0890	-0.1213	-0.3502	0.3910
	(0.0073)	(0.0281)	(0.0291)	(0.2752)		(0.0102)	(0.0526)	(0.0465)	(0.3796)
68	0.0721	0.0135	-0.1675	-1.3377	84	0.0561	-0.2288	-0.1802	1.3382
	(0.0066)	(0.0268)	(0.0278)	(0.3017)		(0.0109)	(0.0564)	(0.0493)	(0.3597)
69	0.0095	0.0865	-0.0661	-0.2964	85	0.0548	-0.0050	-0.2625	0.0476
	(0.0046)	(0.0185)	(0.0199)	(0.1982)		(0.0103)	(0.0517)	(0.0446)	(0.3604)
70	-0.0138	-0.0913	-0.0239	0.1429	86	0.0161	-0.0557	-0.1442	0.8138
	(0.0072)	(0.0258)	(0.0293)	(0.2837)		(0.0092)	(0.0425)	(0.0398)	(0.3696)
71	0.0761	-0.2330	-0.1399	-0.6497	87	0.0680	-0.0053	-0.1764	0.0332
	(0.0065)	(0.0274)	(0.0298)	(0.2908)		(0.0090)	(0.0385)	(0.0383)	(0.3632)
72	-0.0297	0.1009	-0.0821	3.3897	88	0.0144	-0.0670	0.0282	-0.5368
	(0.0097)	(0.0388)	(0.0418)	(0.4094)		(0.0081)	(0.0332)	(0.0356)	(0.2976)
73	0.0618	0.0044	-0.0235	-1.5484	89	0.0191	-0.0623	-0.0467	-0.3809
	(0.0087)	(0.0328)	(0.0349)	(0.3042)		(0.0070)	(0.0223)	(0.0282)	(0.2354)
74	0.0380	0.2734	-0.2390	-1.5872	90	0.0332	0.0712	-0.0807	-1.7982
	(0.0117)	(0.0442)	(0.0463)	(0.3806)		(0.0083)	(0.0266)	(0.0337)	(0.2788)
75	-0.0071	0.1817	-0.1630	-1.4663	91	0.0519	0.1345	-0.1714	-2.5152
	(0.0128)	(0.0467)	(0.0503)	(0.4645)		(0.0094)	(0.0248)	(0.0352)	(0.2730)

Table 8: Steady State Computation of Technology Factors (percent growth rates)

	NIPA 59–73	NIPA '74–91	NIPA '59–91
θ	0.198	0.080	0.113
$\hat{A}$	2.372	0.451	1.387
$\hat{H}$	-0.575	2.102	0.665
$\hat{E}$	-2.059	1.162	-0.155
$\hat{E}$*	-1.439	1.789	0.491
	ASM '59–73	ASM '74–91	ASM '59–91
θ	0.436	0.400	0.297
$\hat{A}$	1.381	-0.861	0.613
$\hat{H}$	0.423	1.303	0.686
$\hat{E}$	-0.888	3.775	0.676
$\hat{E}$*	1.051	8.602	2.779

* Computed assuming quality improvements in K^e based on Gordon.

Appendix: Constructing Value Added TFP

In aggregating to the CPS industry classification, it is necessary to use TFP based on value added rather than on gross output, because gross output does not aggregate simply, and there is not enough information in the NBER's productivity database to aggregate properly. The main problem in constructing value added TFP on the basis of the available data is to convert nominal value added to real. Unfortunately the standard "double deflation" method leads to negative numbers in too many instances, as the computed real cost of materials exceeds the real value of gross output (at least if one uses the deflator for nominal shipments to deflate gross output).

Instead we construct value added TFP directly from gross output TFP as follows. For the sake of exposition, we let gross output Y be a constant returns to scale function of capital K, labor N, and materials M, and we will suppress the industry and time subscripts. Nominal gross output is PY, and the nominal cost of materials is QM. We have

$$TFP_G = \hat{Y} - (\alpha_K \hat{K} + \alpha_N \hat{N} + \alpha_M \hat{M})$$

where α_j is j's factor share in gross output and $\hat{}$ denotes a growth rate. Also we have

$$TFP_V = \hat{V} - (\gamma_K \hat{K} + \gamma_N \hat{N})$$

where $V = Y - M$ and γ_j is factor j's share in value added.

Our key assumption will be that $M \cong \phi Y$, and we will compute ϕ for each industry from its average value of M/Y. Since we know that $\gamma_j(1-\alpha_M) = \alpha_j$, we have

$$TFP_V(1-\alpha_M) \cong \frac{1-\alpha_M}{1-\phi}(\hat{Y} - \phi\hat{M}) - (\alpha_K \hat{K} + \alpha_N \hat{N}).$$

Table 7: Cross–Section Results, 1959–73

$$T\hat{F}P_i = \hat{A} + \bar{\alpha}_i^s \hat{H}^s + \bar{\alpha}_i^u \hat{H}^u + \bar{\alpha}_i^e \hat{E} + \bar{\alpha}_{it}^m \hat{X}$$

	$\hat{A}$	$\hat{H}_s$	$\hat{H}_u$	$\hat{E}$	$\hat{X}$	R^2
OLS	0.0079	0.0197				0.0030
	(0.0016)	(0.0169)				
WLS	0.0131	-0.0137				0.4653
	(0.0009)	(0.0077)				
WLS	0.0209	-0.0100	-0.0444			0.4992
	(0.0017)	(0.0075)	(0.0081)			
WLS	0.0195	-0.0145	-0.0448	0.0160		0.5007
(equip.)	(0.0020)	(0.0085)	(0.0081)	(0.0135)		
WLS	0.0165	-0.0202	-0.0433	0.0249		0.5100
(total)	(0.0021)	(0.0081)	(0.0080)	(0.0079)		
WLS	0.1016	-0.0979	-0.1234	-0.1143	-0.0856	0.5254
(equip.)	(0.0017)	(0.0192)	(0.0182)	(0.0302)	(0.0178)	

1974–91

OLS	0.0037	-0.0165				0.0028
	(0.0016)	(0.0148)				
WLS	-0.0030	0.0690				0.0567
	(0.0029)	(0.0195)				
WLS	0.0266	0.0590	-0.1644			0.1413
	(0.0052)	(0.0187)	(0.0248)			
WLS	0.0461	0.0897	-0.1781	-0.1466		0.1726
(equip.)	(0.0070)	(0.0198)	(0.0246)	(0.0358)		
WLS	0.0498	0.0926	-0.1913	-0.1017		0.1793
(total)	(0.0072)	(0.0081)	(0.0250)	(0.0224)		
WLS	-0.0546	0.1969	-0.0872	0.0047	0.1043	0.1793
(equip.)	(0.0528)	(0.0595)	(0.0535)	(0.0868)	(0.0546)	

Consequently we have

$$TFP_V(1-\alpha_M) \cong TFP_G - (\hat{Y} - \alpha_M\hat{M}) + \frac{1-\alpha_M}{1-\phi}(\hat{Y} - \phi\hat{M})$$

or

$$TFP_V \cong \frac{1}{(1-\alpha_M)}TFP_G - \frac{1}{(1-\alpha_M)}(\hat{Y} - \alpha_M\hat{M}) + \frac{1}{1-\phi}(\hat{Y} - \phi\hat{M}).$$

Here everything varies both over industry and time, except for ϕ, which only varies over industries. This was constructed at the 4–digit level and then aggregated weighting by $Y - \phi M$.

We should stress that the results were not sensitive to alternative methods of dealing with this problem. Various constructs of TFP_V were all highly correlated with each other, and with TFP_G. (The correlation of this construct with TFP_G is 0.93.)

References

[1] Berman, Eli, J. Bound, and Z. Griliches, "Changes in the Demand for Skilled Labor within U.S. Manufacturing: Evidence from the Annual Survey of Manufactures," *Quarterly Journal of Economics* 109 (February 1994).

[2] Dunne, Timothy, J. Haltiwanger, and K. Troske, "Technology and Jobs: Secular Changes and Cyclical Dynamics," NBER Working Paper No. 5656, July 1996.

[3] Gordon, Robert, *The Measurement of Durable Goods Prices*, University of Chicago Press, 1990.

[4] Greenwood, Jeremy, Z. Hercowitz, and P. Krusell, "Long–Run Implications of Investment–Specific Technological Change," RCER Working Paper No. 420, June 1996.

[5] Greenwood, Jeremy and M. Yorukoglu, "1974," RCER Working Paper No. 429, September 1996.

[6] Hornstein, Andreas, and P. Krusell, "Can Technology Improvements Cause Productivity Slowdowns," manuscript, 1996.

[7] Kahn, James, and J.–S. Lim, "On the Contribution of Human Capital to Growth," manuscript, 1994.

[8] Katz, Lawrence, and K. Murphy,"Changes in Relative Wage, 1963–1987: Supply and Demand Factors," *Quarterly Journal of Economics* 107 (February 1992).

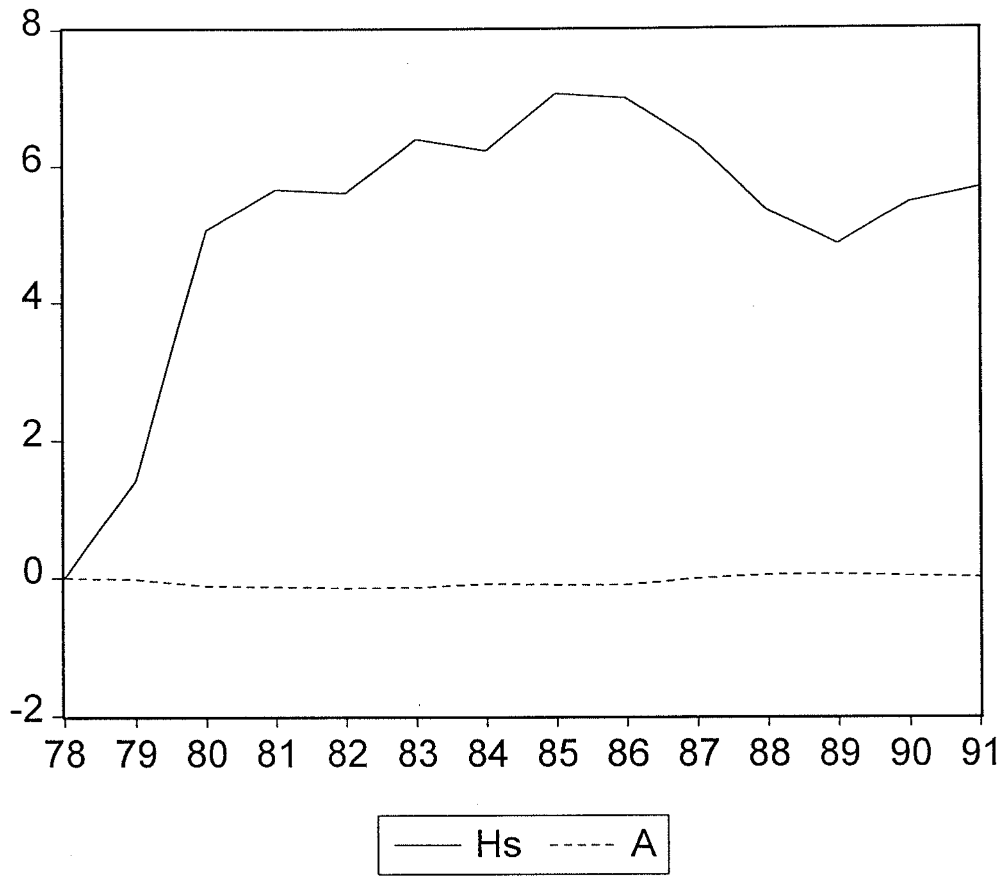
[9] Klenow, Peter, "Ideas vs. Rival Human Capital: Industry Evidence on Growth Models," manuscript, 1996.

[10] Kremer, Michael, and E. Maskin, "Segregation by Skill and the Rise in Inequality, Hoover Institution Working Paper E–95–7 (June 1995).

[11] Krusell, Per, L. Ohanian, V. Rios–Rull, and G. Violante, "Capital–Skill Complementarity and Inequality," manuscript, 1996.

[12] Murphy, Kevin, and F. Welch, "The Structure of Wages," *Quarterly Journal of Economics* 107 (February 1992).

Figure 1: Components of TFP



Contribution to TFP

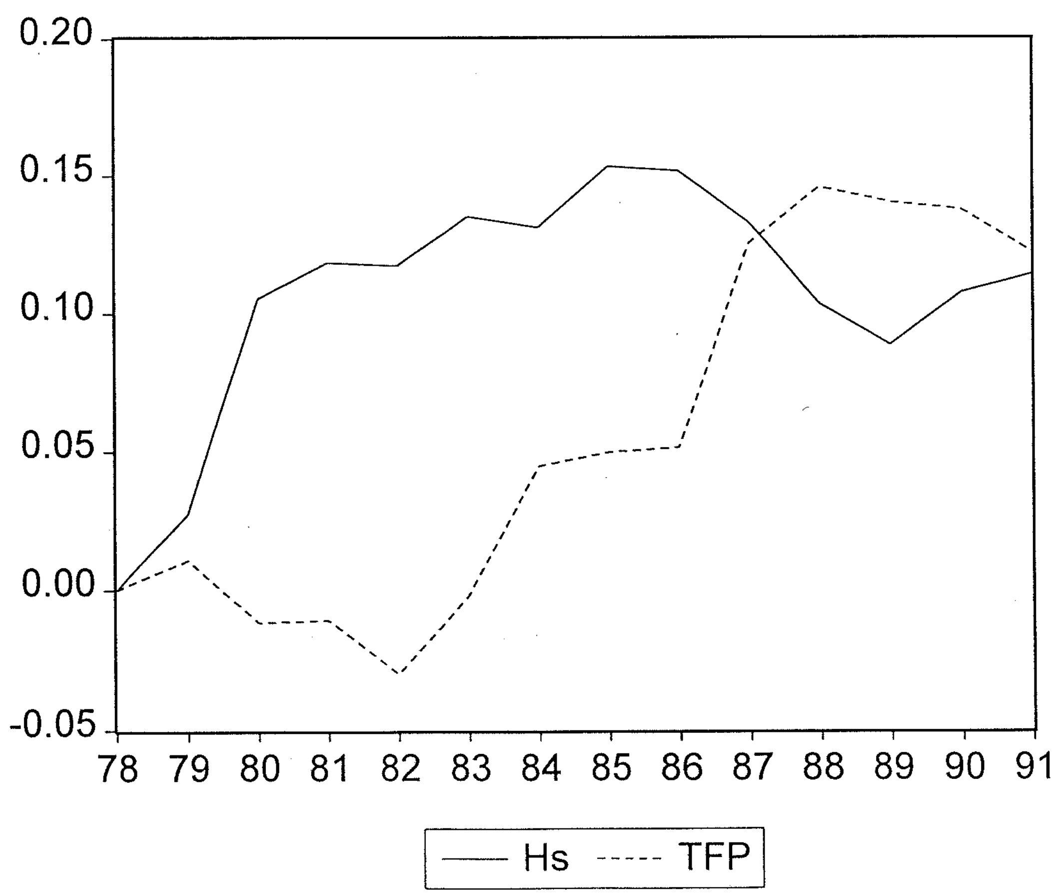
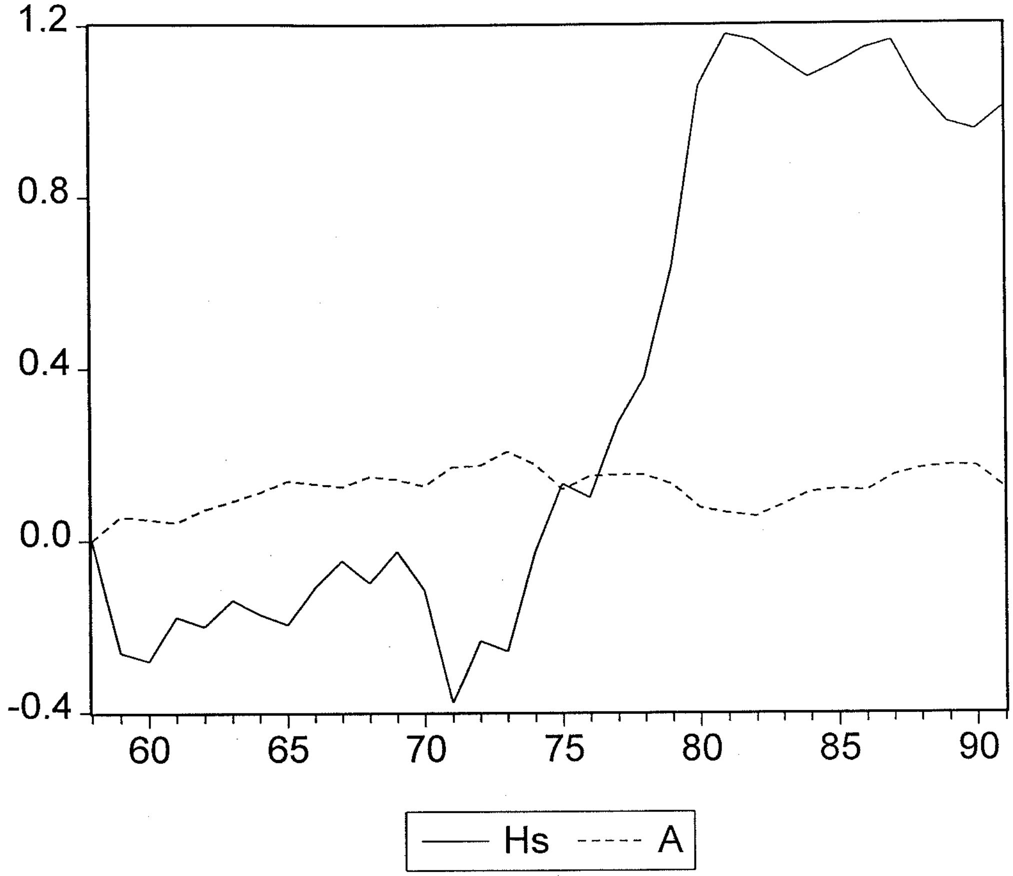


Figure 2: Components of TFP, MP Dataset



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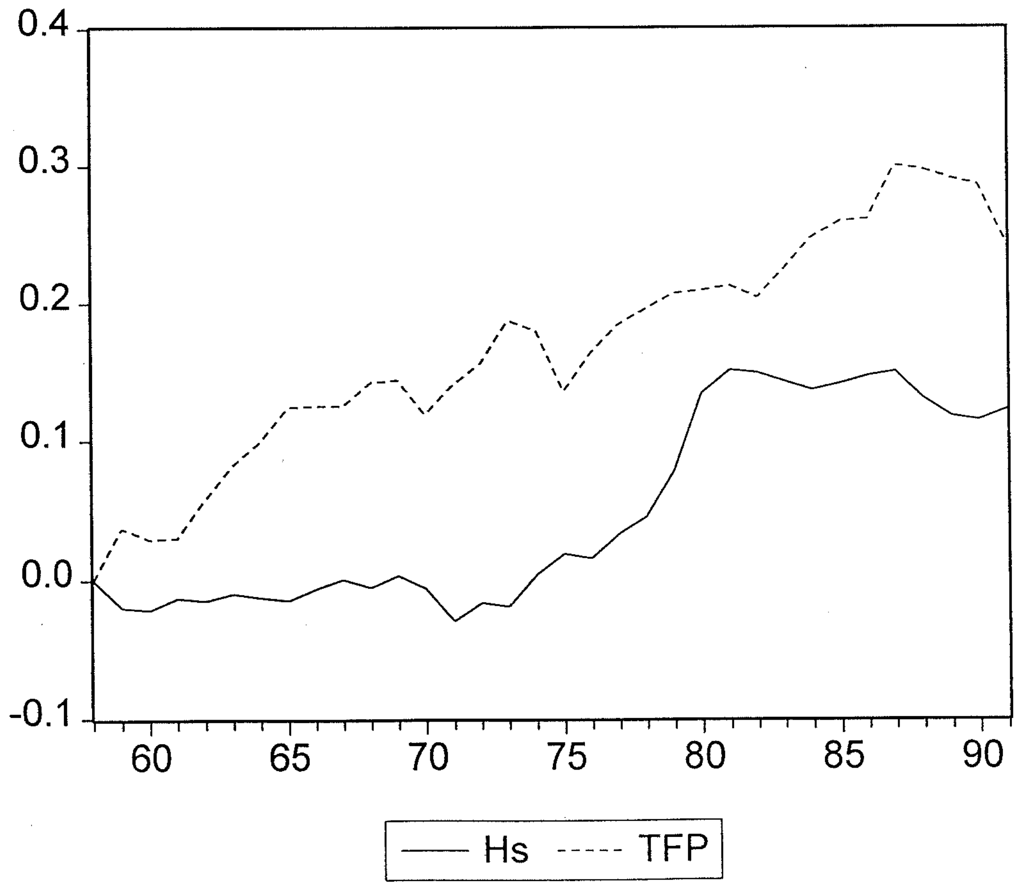

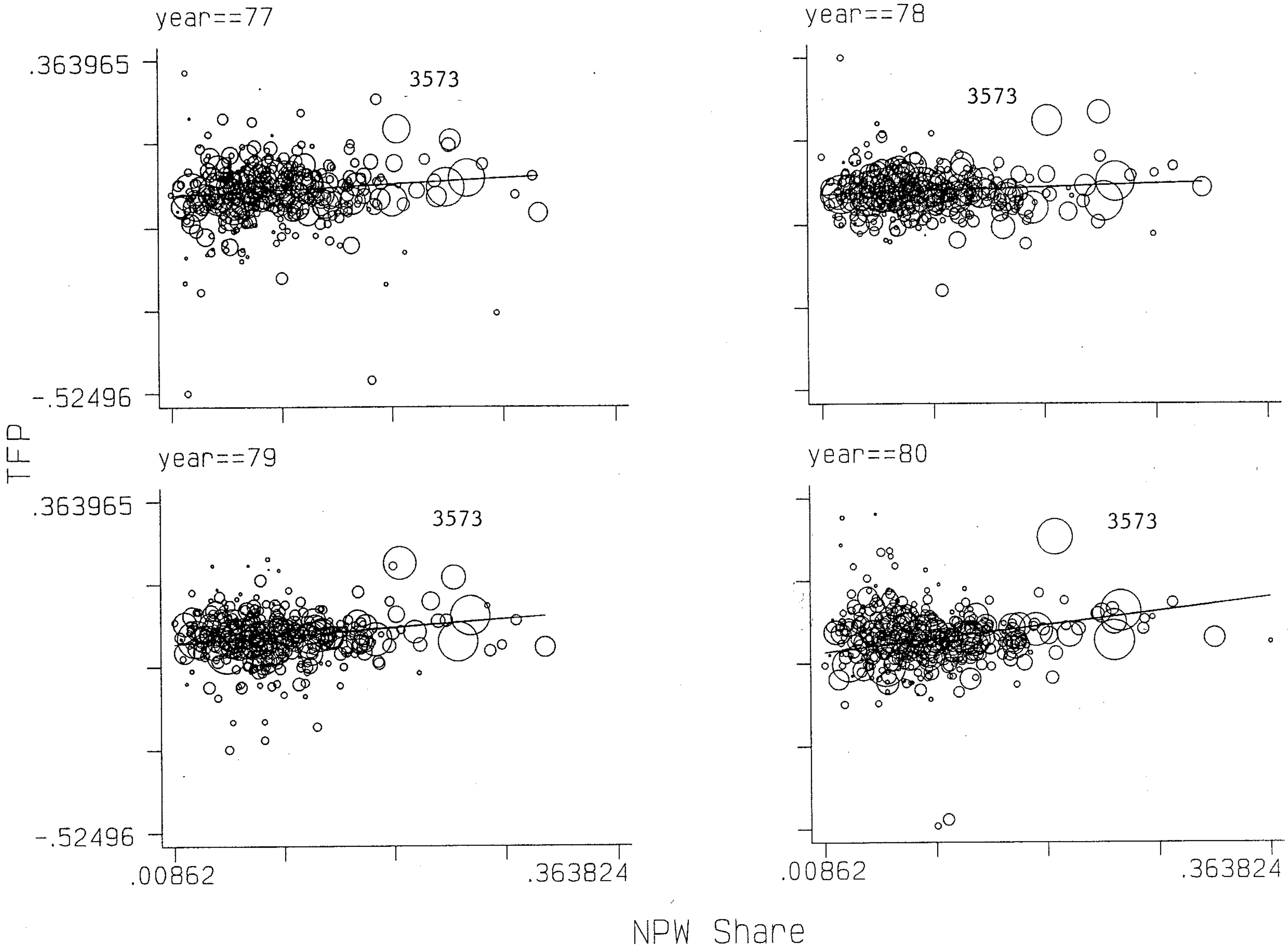
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NPW Share

FIGURE 3

Figure 4: Contributions of Skilled Labor and Capital to TFP Growth

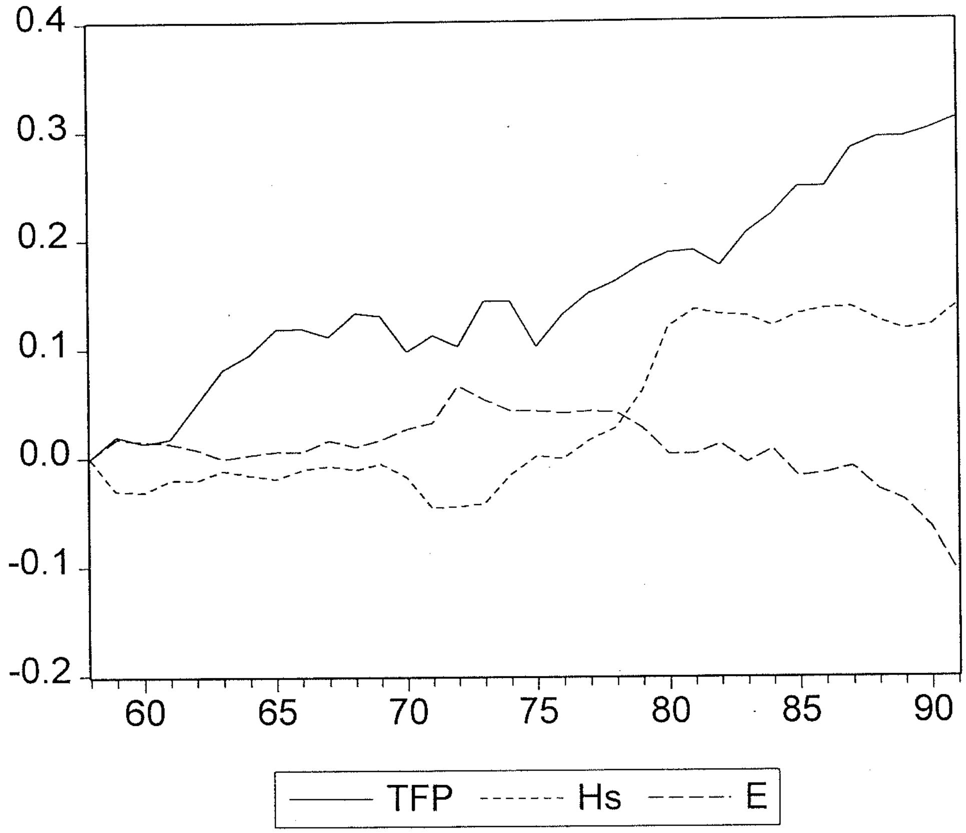

Figure 5: Contributions of Skilled Labor with Embodied Technical Change in Equipment