SKILLED LABOR-AUGMENTING TECHNICAL PROGRESS IN U.S. MANUFACTURING*

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First draft October 1996, this draft June 1998

Abstract

This paper examines the role of skilled labor in the growth of total factor productivity. We use panel data from manufacturing industries to assess the extent to which productivity growth in yearly cross–sections is tied to industry shares of skilled labor inputs. We find robust evidence that productivity growth was increasingly concentrated in high-skill industries during a unique 10-year period beginning in the early 1970s. We do not find any positive association of productivity growth with new capital investment.

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I. Introduction

There is increasing evidence that the last 25 years has witnessed a dramatic change in the way goods are produced. During this period firms began to replace relatively unskilled workers by skilled workers and equipment at an unprecedented rate. This was not due merely to the increased availability of skilled labor, since the relative wages of skilled workers increased dramatically along with their employment. Rather, the patterns of wages and employment suggest technical change resulting in increased demand for skilled labor. This process of *skill–biased technical change* is regarded by many as a primary force behind the increased dispersion of the distribution of income during the same time period.[1]

The focus of much of this evidence has been on patterns of wages and employment across industries and demographic groups. In this paper we examine the phenomenon of technical change from another angle by looking directly at total factor productivity (TFP) growth. What we will call *skilled labor–augmenting technical progress*—an increase in the effective labor input of skilled workers—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, which implies that productivity growth will be greater in industries that make intensive use of engineers and statisticians. Furthermore, since skilled labor–augmenting technical progress can induce skill–biased technical change (SBTC)—under conditions that we suggest are present in U.S. manufacturing—a finding of skilled labor–augmenting technical progress could "explain" the acceleration of SBTC. In any case, it offers additional independent evidence of unusual structural change during this time period.

Specifically, we examine the relationship between productivity growth and skill intensity

[1] Competing explanations include sector bias (e.g. Haskel and Slaughter [1998]) or outsourcing (e.g. Feenstra and Hanson [1997]). The latter find ambiguous evidence on the relative importance of technology and trade.

in manufacturing industries over the period 1958–1991. We find strong evidence that productivity growth was increasingly concentrated in the more skill–intensive manufacturing industries during a unique period of approximately ten years beginning in the early 1970s. This skilled labor effect, which we identify as skilled labor–augmenting technical progress, accounted for essentially all of productivity growth in manufacturing during that period. Surprisingly, we find no evidence of any similar effects from capital, capital equipment, or new investment in capital or equipment. Though more work is necessary, this would seem to cast doubt on stories that stress plant retooling or new computer technology as the *sine qua non* of technical change.

The results in this paper thus contribute to a large empirical literature on technical change and its impact on employment and wage 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 1959–1989, with an acceleration after 1979. They also show that much of this increase occurred within industries, and therefore does not represent the effect of shifts in product demands. Autor, Katz, and Krueger [1997] make the same claim based on decomposition of college–educated employment and wage bill data into between and within–industry effects. Dunn, Haltiwanger, and Troske [1996] carry this point one step further and provide evidence 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. . . ."

On the wage front, 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. 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.[2] Bound and Johnson [1992] use microeconomic data on wages to quantify the relative importance of various explanations for changes in the structure of wages, and argue that biased technical change is the major cause.

With all of these findings regarding wages and employment as background, then, it seems natural to examine productivity as a more direct measure of the technical change that is allegedly responsible. The next section develops the analytical framework, which is based on a straightforward extension of standard growth accounting. Section III introduces the data and empirical results. Section IV concludes.

II. The Model

A. Technology

For convenience we follow common practice and divide workers into two broad categories: "skilled" and "unskilled," though obviously the analysis generalizes to more than two types. We define skilled labor–augmenting technical progress as an advance in knowledge that increases the effective labor input of skilled workers by more than that of unskilled workers. For example, new computer software that enables skilled labor to increase the amount of work they can do, but that is not used by unskilled labor, would fit into this category. 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 differentiable,

[2] Murphy and Welch [1992] also document drmatic increases in the wage premium of college relative to high school graduates.

constant returns to scale production technology that in its most general form we specify as:

$$Y_{it} = A^*_{it} F_i(K^p_{it}, K^e_{it} A^e_t, N^s_{it} A^s_t, N^u_{it} A^u_t), \tag{1}$$

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

$$Y^+_{it} = A^*_{it} F_i(K^p_{it}, K^e_{it} A^e_t, N^s_{it} A^s_t, N^u_{it} A^u_t, M_{it} A^m_t), \tag{2}$$

where Y^+_{it} is gross output, and M_{it} is a vector of material inputs. For the sake of exposition we will proceed using (1), as the extension to (2) is straightforward.

The various terms multiplying the inputs represent increases in the effective input per physical unit. Thus, for example, A^s_t represents the effective input per skilled worker. As will be clear below, identification requires that they be independent of i and that there be no augmentation of at least one of the factors (in this case K^p, though in the empirical work we will consider a variety of alternatives). We will discuss these and other issues surrounding the interpretation of these variables as we go along. Note also that the production function differs by industry, and that the Hicks–neutral technology shifter A^*_{it} has both an aggregate and industry–specific component. We assume that the firm is competitive, and faces market wages W^s_t and W^u_t, rental prices of plant and equipment Q^p_t and Q^e_t, and output prices $\{P_{it}\}$. We require no other assumptions about the form of the production function.

The firms face the following static optimization problem:

$$\underset{K^p_{it}, K^s_{it}, N^s_{it}, N^u_{it}}{\text{Max}} \; P_{it} A^*_{it} F_i(K^p_{it}, K^e_{it} A^e_t, N^s_{it} A^s_t, N^u_{it} A^u_t) - Q^p_t K^p_{it} - Q^e_t K^e_{it} - W^s_{it} N^s_{it} - W^u_{it} N^u_{it} \tag{3}$$

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

$$
\begin{aligned}
P_{it}A^*_{it}F_{1i}(K^p_{it}, K^e_{it}A^e_t, N^s_{it}A^s_t, N^u_{it}A^u_t) &= Q^p_t \\
P_{it}A^*_{it}F_{2i}(K^p_{it}, K^e_{it}A^e_t, N^s_{it}A^s_t, N^u_{it}A^u_t) &= Q^e_t/A^e_t \\
P_{it}A^*_{it}F_{3i}(K^p_{it}, K^e_{it}A^e_t, N^s_{it}A^s_t, N^u_{it}A^u_t) &= W^s_t/A^s_t \\
P_{it}A^*_{it}F_{4i}(K^p_{it}, K^e_{it}A^e_t, N^s_{it}A^s_t, N^u_{it}A^u_t) &= W^u_t/A^u_t
\end{aligned}
\qquad \forall i, t \tag{4}
$$

The factor shares at each point in time are denoted α^h_{it}, where $h = p, e, s, u$. Competition and constant returns to scale imply, for example,

$$
\alpha^p_{it} = \frac{Q^p_t K^p_{it}}{P_{it}Y_{it}} = \frac{F_{1i}(\cdot)K^p_{it}}{F(\cdot)}, \tag{5}
$$

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. Taking a first–order approximation of the production function at t relative to $t-1$, we have

$$
\begin{aligned}
\Delta \ln Y_{it} \;\; \cong \;\; & \Delta \ln A^*_{it} + \alpha^p_{it-1}\Delta \ln K^p_{it} + \alpha^e_{it-1}(\Delta \ln K^e_{it} + A^e_t) \\
& \alpha^s_{it-1}(\Delta \ln N^s_{it} + \Delta \ln A^s_t) + \alpha^u_{it-1}(\Delta \ln N^u_{it} + \Delta \ln A^u_t).
\end{aligned} \tag{6}
$$

Redefining $\Delta \ln A^*_{it} \equiv \Delta \ln A^*_t + \epsilon_{it}$, with $E(\epsilon_{it}) = 0$, this implies that TFP growth satisfies the following:

$$
\Delta \ln TFP_{it} \cong \Delta \ln A^*_t + \alpha^e_{it-1}\Delta \ln A^e_t + \alpha^s_{it-1}\Delta \ln A^s_t + \alpha^u_{it-1}\Delta \ln A^u_t + \epsilon_{it}. \tag{7}
$$

Here ϵ_{it} has the interpretation of an industry–specific Hicks–neutral technology shock, while $\Delta \ln A^*_t$ (no industry subscript) represents an aggregate Hicks–neutral shift in the production function.

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^*, A^e, A^sor A^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 have in mind that factor intensity (as measured by factor shares) is a more or less fixed characteristic of an industry—not that it cannot change over time, but that it is pre–determined as far as an equation like (7) is concerned. (This would be the case if each industry had Cobb–Douglas production with different factor share parameters, provided technical progress is of the factor–augmenting variety.) Even though firms continue to choose factor proportions optimally, growth in A^s (for example) is in our approach essentially an exogenous event that has differential effects on TFP across industries depending on their skilled labor shares.

It should be noted that this approach might not distinguish between factor–augmenting technical progress and improvements in the quality of factors or inputs. For capital this may not be an important distinction (presumably most changes in A^e are changes in the quality of capital, 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, A^s could grow because workers themselves are better–educated, or because advances in knowledge increase their effective input relative to that of other factors. 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 A^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. The former could, for example, come from the inspiration of a single genius, while the latter would require educating or training the industry's entire labor force sufficiently to change its average human capital.

B. Skill–Biased Change versus Skill–Augmenting Change

A common approach in the technical change literature has been to define *skill–biased* technical change as an increase in skilled labor's cost share (ideally after controlling for the effects of changes in relative factor prices: see, for example, Binswanger [1974]). This phenomenon in itself is a "black box"—that is, it does not convey much about the underlying cause of the change. It also, of course, is consistent with a variety of changes in relative factor prices and quantities. The SBTC observed in U.S. labor market data has been associated with an increase in the relative price of skilled labor, and has been interpreted by a number of researchers as an outward shift in the demand for skilled labor.

Skilled labor–augmenting technical change as defined here is arguably a "deeper" phenomenon, but it is not uniquely related to changes in factor shares. This is obvious in the case of a Cobb–Douglas production function, which by definition has factor shares that are constant with respect to factor–augmenting technical change.[3] If, however, the elasticity of substitution between skilled and unskilled labor exceeds one (for which we will argue there is favorable evidence), then skilled labor–augmenting technical change will be associated with increased demand for skilled labor (that is, SBTC).

To illustrate this, consider a CES industry production function, with factor augmentation in equipment, skilled, and unskilled labor. Letting σ denote the elasticity of substitution, and defining $\theta = 1/\sigma$, we have

$$(8) \qquad y_{it} = A^*_{it}[\alpha^p_i(K^p_{it})^{1-\theta} + \alpha^e_i(K^e_{it}A^e_t)^{1-\theta} + \alpha^s_i(N^s_{it}A^s_t)^{1-\theta} + \alpha^u_i(N^u_{it}A^u_t)^{1-\theta}]^{\frac{1}{1-\theta}},$$

where $\Sigma_k \alpha^k_i = 1$ and $\theta > 0$. From the first–order conditions we have

[3] Indeed, the concept of factor–augmentation in the Cobb–Douglas case with a single time–series is not meaningful. It is only the cross–sectional dimension (with variation in factor shares across industries) that makes identification possible.

$$\begin{aligned} \hat{P}_i + \theta(\hat{y}_i - \hat{N}_i^s) + (1-\theta)(\hat{A}^* + \hat{A}^s) &= \hat{W}^s \\ \hat{P}_i + \theta(\hat{y}_i - \hat{N}_i^u) + (1-\theta)(\hat{A}^* + \hat{A}^u) &= \hat{W}^u, \end{aligned} \tag{9}$$

where a "ˆ" over a variable denotes a growth rate. Cobb–Douglas production is of course the special case in which $\sigma = \theta = 1$.

From the system (9) we can isolate the relationship between skilled labor–augmenting technical progress and SBTC. From the equations for skilled and unskilled labor we have

$$\hat{N}_i^s - \hat{N}_i^u = (\sigma - 1)(\hat{A}^s - \hat{A}^u) - \sigma(\hat{W}^s - \hat{W}^u) \tag{10}$$

for within–industry changes in relative labor demand. For the relative change in skilled labor's share we get

$$\hat{N}_i^s - \hat{N}_i^u + \hat{W}^s - \hat{W}^u = (\sigma - 1)[(\hat{W}^u - \hat{A}^u) - (\hat{W}^s - \hat{A}^s)]. \tag{11}$$

Analogous equations obtain for other relative shares (e.g. skilled labor relative to equipment). The term on the right–hand side should have the same sign as $\sigma - 1$ in response to $\hat{A}^s$, since an augmentation of skilled labor must (*ceteris paribus*) reduce its wage per effective unit W^s/A^s. Thus growth in A^s corresponds to SBTC (in the sense of a change in relative factor shares) provided that $\sigma > 1$. This result extends to more general production functions, at least locally. Although there is considerable uncertainty regarding the appropriate choice of σ in this context, recent work has centered on values that exceed one (e.g. Katz and Murphy [1992], Bound and Johnson [1992]).

III. Empirical Implementation

A. Data

We limit the scope of our study to manufacturing primarily because of data availability, and because we suspect that productivity in particular is better measured in manufacturing than in other sectors. Our data come from two main sources: The Annual Survey of

Manufacturers (ASM) and Current Population Survey (CPS). We will make most extensive use of the National Bureau of Economic Research's manufacturing productivity (MP) database, which is based on the ASM but includes a measure of gross output–based total factor productivity (TFP) growth annually by industry. As a check of the results, we will also compare findings based on merging the MP dataset with the CPS outgoing rotation data set, which contains information on workers' education levels, earnings, and industry of employment. Appendix 2 provides additional details about data sources and construction.

From the MP dataset we obtain 4–digit industry data on TFP 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. We measure skilled labor's share based on the earnings share of non–production workers. In computing labor's share for each industry, we multiplied 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 (NIPA) data. (The results are not sensitive to this adjustment.)

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

$$(r+\delta_i^e)K_{it}^eQ_t^e/[(r+\delta_i^e)K_{it}^eQ_t^e+(r+\delta_i^p)K_{it}^pQ_t^p)] \tag{12}$$

for industry i in year t, where δ_i^p and δ_i^e are industry–specific depreciation rates for plant and equipment. We simply set r to be a constant 0.04, as the results are not sensitive to specifications of variables that do not vary cross–sectionally. Figure I plots the behavior of the key factor shares over the sample period. Production labor's share appears to have a steady slight decline throughout (though accelerating slightly beginning in the late 1970s), while the shares of equipment and non-production labor begin to rise in the mid–1970s. Note that equipment's share begins to increase somewhat before non–production workers' share.

Using these factor shares and TFP growth rates, we can estimate equations such as (7) for the entire 1958–1991 sample period with a panel of 449 4–digit industries. The only skill distinction for this dataset, however, is between non–production and production workers. As a check on the validity of this distinction, we merge the above with data culled from the CPS outgoing rotation survey, which has data on individual workers' industry, education level, and earnings, over the period 1979–1991. From these we 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 use 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 consider other thresholds as well.

Merging the CPS data with MP dataset (in order to get TFP growth and other factor shares) presents two difficulties. First, 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 66 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."

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 Appendix 1), so the factor shares for that portion of the empirical work are shares of value added rather than gross output.

One benefit from examining the CPS data is being able to compare different definitions of skilled labor. Researchers have commonly used the production worker/non–production worker distinction (e.g. 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 it turns out that we find a high correlation and similar econometric results, in the end we stress the MP data, which have the advantages of greater disaggregation and a longer sample period.

B. Identification and Estimation

The focus of the paper will be on the patterns of growth in A^s. To that end, we will first proceed under the assumption that $A^e_t = A^u_t = A^m_t = 1 \ \forall t$, i.e. that all inputs except skilled labor are measured accurately in efficiency units. This is just to establish a simple benchmark case, which we will generalize in various directions to see how the initial results hold up. Thus (7) becomes

$$\Delta \ln TFP_{it} = \Delta \ln A^*_t + \alpha^s_{it-1} \Delta \ln A^s_t + \epsilon_{it}. \tag{13}$$

If skilled labor's share α^s_{it} is uncorrelated with ϵ_{it} in the cross–sections, then a period–by–period regression of TFP growth on α^s_{it} will yield estimates of $\Delta \ln A^s_t$ and $\Delta \ln A^*_t$ for each t. 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.[4]

Note that by assuming that ϵ_{it} is uncorrelated with α^s_{it}, we are essentially labeling as "skilled labor–augmenting" any growth in TFP that is systematically related in the data to

[4] One strength of this approach is that even if TFP growth is not measured very accurately, since it is the dependent variable in the regression, classical measurement error is not a problem.

skilled labor's share. (Below we will control for other factor shares as well.) It therefore lumps together true skilled labor–augmenting technical progress (growth in A^s) with sector–biased Hicks–neutral technical progress (growth in A^*_{it} that is correlated with α^s_{it}). This suggests an alternative—less structural—interpretation of this exercise: The estimated values of $\Delta \ln A^s_t$ can be thought of as the combined effects of skilled labor–augmenting and sector–biased technical progress. Thus even if the estimates of $\Delta \ln A^s_t$ are contaminated by the presence of sector–biased technical change, they will still be informative about changes in the patterns of TFP growth across industry and over time. While bearing in mind this more agnostic interpretation, we will continue (except as noted) to refer to the estimates of $\Delta \ln A^s_t$ as skilled labor–augmenting technical progress.

Part of our strategy will therefore be to use the annual regression results as a guide to direct us toward trends or structural breaks in the data, as opposed to interpreting them literally as year–by–year estimates of these effects. After presenting a range of 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 1958–1991 data set). Thus whether or not one accepts the structural interpretation of the statistics, the evidence for such a break in the association between skill–intensity and TFP growth stands on its own. 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 within any one industry (the results were not sensitive to this assumption), whereas skilled labor's share varies across both industries and time. There is in fact considerable growth over time in our measures of skilled labor's share, as we saw in Figure I.

C. Results

Our first exercise is to estimate (13) on the MP dataset, 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 we present are Weighted Least Squares estimates using industry employment as the weight. There are several 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 aggregates of smaller industries. Second, since this is primarily a history paper, i.e. we want to know what forces shaped the economy over a particular historical episode, it makes sense to give more weight to larger industries. Third, there appears to be heteroscedasticity in the data, with the residual variance inversely related to size, as one might expect if the data from the smallest industries are noisier.

The results of this exercise are in Table I, using the non–production labor definition of skilled labor. The results indicate a surge in skilled labor–augmenting technical progress unique to the period from approximately 1972 to 1981. Since the regression results are a lot to absorb, we also provide a time plot related to the estimated coefficients. Figure II is a plot of the contribution of A^s to total TFP. This was computed by multiplying the estimated growth in A^s for each year by that year's mean of α^s_{it} and accumulating over time. Total TFP is represented by adding to the contribution of A^s the estimated growth in A. There is essentially no growth in A^s until 1972. It then grows dramatically from then until 1981 (contributing a remarkable 1.44 percent annually to TFP growth for these nine years), and then levels off. Thus the relatively steady growth of overall productivity (the dashed line in the figure) conceals dramatic underlying shifts in the relationship between it and labor force composition. It is interesting to note that the onset of the growth in A^s is close to when equipment's share began to grow (see Figure I), and actually preceded overall growth in skilled labor's share. This suggests a potential role for equipment in the story, but we will investigate that separately below.

To verify that the results are not too sensitive to outliers, regressions were also run alternately omitting industry 3573 (electronic computing) and 2711 (newspaper printing and publishing). The former has extremely high TFP growth during most of the sample, and an above–average skilled labor share, while the latter experienced negative TFP growth with an above–average skilled labor share. It turns out that 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. Omitting industry 2711, on the other hand, makes the results stronger.[5]

Figure III illustrates this further with weighted scatter diagrams of TFP growth and non–production worker shares for the years 1977–1980, together with the regression line from Table I, in order to show that the results are not driven by one or two outliers. For example, 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 modest influence on the regression results. The figure also indicates industry 2711, which more than offsets the influence of the computer industry.

We then examine 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 regression results are provided in Table II for four different skill definitions. 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 $\Delta \ln A^s$ provides the coefficients on skilled labor's share α^s_{it}, while the column labeled $\Delta \ln A^*$ has the coefficients on a constant and 12 year dummies. Consistent with the results from the MP data, there appears to be dramatic growth in A^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

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

began. The t–statistics from the regression show that the initial growth in A^s is statistically significant. The results say, for example, that an industry with a skilled labor share of 0.09 in 1979 (approximately the 80th percentile) would have seen its TFP increase by a factor of $-0.037 + 0.09 \cdot 0.601 = .017$ or about 1.7 percent that year. On the other hand, an industry with a 0.035 share of skilled labor (approximately the 20th percentile) would have seen a *decline* in TFP growth of about 1.6 percent.

The remaining results in Table II examine alternative skill definitions. 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 effects are insignificant for the 12–year cutoff. This is not surprising, since the evidence of skill–biased technical change has been based on the market for college–educated relative to high school–educated workers. Thus lumping both groups together would muddle the distinction. Indeed, the fact the result is weaker for this broader definition strengthens the link between these findings and the other literature on skill–biased technical change.

Table III shows the correlations of four different measures of skilled labor's share. These are correlations from the cross–section of industry averages, weighted by industry employment. Here the main thing to notice is that the share of non–production worker earnings is strongly correlated to the two higher education–based measures. Thus for the purposes of this investigation, at least, defining skilled labor as non–production labor appears to be reasonable.

D. The Role of Other Inputs

Next we extend the analysis to incorporate analogous effects through other inputs. There are several possibilities here, depending on the treatment of capital: Technical change can be tied to equipment and/or structures, and can be embodied or disembodied. The simplest specification has capital–augmenting technical progress:

$$\Delta \ln TFP_{it} = \Delta \ln A_t^* + \alpha_{it-1}^s \Delta \ln A_t^s + \alpha_{it-1}^u \Delta \ln A_t^u + \alpha_{it-1}^k \Delta \ln A_t^e + \epsilon_{it}, \tag{14}$$

where $\alpha_{it}^k = \alpha_{it}^p + \alpha_{it}^e$. The material share effect $\Delta \ln X_t$ is normalized to zero.

Capital augmentation can be interpreted as allowing for mismeasurement of quality improvements in capital, but it does not distinguish between vintages or between plant and equipment. If technical progress were only embodied in new capital, and industry investment were not proportional to its capital share, then we would possibly miss some growth in A_t^e by using α_{it}^k. 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 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 $\Delta \ln A_t^e$.

Alternatively, we can replace capital's share by equipment's share to allow for the possibility that technical change is primarily associated with equipment rather than total capital. Perhaps more realistically still, we can allow for technical change that is embodied only in new capital. Most stories about SBTC center around plant retooling or expansion. Dunne, Haltiwanger, and Troske [1996], for example, provide evidence that changes in non–production workers' shares 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 (that is, $K = K^p + K^e$), for the sake of exposition.

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

$$K_t^* = K_{t-1}^*(1-\delta) + I_{t-1}Z_{t-1} \tag{15}$$

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 $\Delta \ln A_t^e = \Delta \ln K_t^* - \Delta \ln K_t$ by definition. And we have

$$\Delta \ln K_t = -\delta + I_{t-1}/K_{t-1} \tag{16}$$

$$\Delta \ln K_t^* = -\delta + I_{t-1}Z_{t-1}/K_{t-1}^* = -\delta + \frac{I_{t-1}Z_{t-1}}{K_{t-1}A_{t-1}^e}, \tag{17}$$

which implies that $\Delta \ln A_t^e = (I_{t-1}/K_{t-1})(Z_{t-1}/A_{t-1}^e - 1)$. Consequently, an alternative specification of (14) that treats new technology as embodied in new capital is

$$\Delta \ln TFP_{it} = \Delta \ln A_t^* + \alpha_{it-1}^s \Delta \ln A_t^s + \alpha_{it-1}^k (I_{it-1}/K_{it-1})(Z_{t-1}/A_{t-1}^e - 1) + \epsilon_{it}, \tag{18}$$

where α^k is capital's share. (Note that from (15) we have $K_t^* = \sum_{\tau=1}^{\infty}(1-\delta)^\tau I_{t-\tau}Z_{t-\tau}$, which implies that

$$A_t^e = \frac{\sum_{\tau=1}^{\infty}(1-\delta)^\tau I_{t-\tau}Z_{t-\tau}}{\sum_{\tau=1}^{\infty}(1-\delta)^\tau I_{t-\tau}} \tag{19}$$

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.) This is the same equation as (14) except that $\alpha_{it-1}^k(I_{it-1}/K_{it-1})$ replaces α_{it-1}^e on the right–hand side. Since in general one would expect I_{it-1}/K_{it-1} to be correlated with ϵ_{it} (presumably part of ϵ_{it} is observable by those who are choosing I_{it-1}), it would be necessary to use instrumental variables. By the same argument that made factor shares reasonable exogenous variables, we can use factor shares as instruments for $\alpha_{it-1}^k(I_{it-1}/K_{it-1})$.

Finally, given the timing of the estimated skilled labor augmentation, one might suspect that energy prices might have played some role. For example, suppose industries that have relatively high energy cost shares reduce their capital utilization (and hence their TFP) in response to an increase in the price of energy. If energy cost shares are positively correlated with production labor shares, then the estimates of $\hat{A}_t^s$ could be strongly upward–biased in years with big energy price increases. It turns out, however, that the year–to–year estimates of $\hat{A}_t^s$ are very similar when energy's share is included, even though energy's share does enter significantly in the years in question.

It turns out that for all of these various specifications, the basic pattern in Table I and Figure II for skilled labor augmentation remains, while no evidence of comparable effects for other factors emerges. If anything the other factor–augmentation effects show up as negative, particularly the unskilled labor effect. The results reported in Table IV using embodied improvement in total capital (equation (18)) are representative. They show little evidence of a substantial role for such equipment effects, while the skilled labor effects are quite similar to those from Table I—if anything they persist later into the 1980s. One interpretation of this is that even if capital improves in quality, productivity improves only to the extent that skilled labor is present. In fact, the results go further than that, suggesting that new equipment in the absence of skilled labor has an adverse impact on productivity. This could be a consequence of learning effects or adjustment costs (as in Hornstein and Krusell [1996]), though clearly more work is needed to understand this puzzle.

One striking aspect of Figure II is that by and large, overall TFP growth appears unaffected by the massive underlying shifts in the relative importance of skilled labor versus other factors. In other words, the breakdown of TFP growth into factor–augmentation components is virtually a zero–sum game: During the period of high skilled labor–augmenting change there is relatively less Hicks–neutral technological progress and/or progress via augmentation of other factors, so TFP growth does not accelerate. Even with the more agnostic interpretation of this episode as some combination of skilled–labor augmenting and sector–biased Hicks–neutral technical progress, it is still surprising that there is no apparent aggregate effect.

Why should this be? One explanation is that whatever the underlying structural changes in the economy, the overall resources devoted to technological progress do not change very much, at least in the short run. How and where those resources are allocated, on the other hand, may respond to short–run changes in economic conditions. For example, a large influx of unskilled labor might induce firms to focus their innovation energies on improvements in the capital that unskilled labor works with. This would include organizational changes such as the assembly line. The early 1970s did witness a large increase in the supply of skilled labor due to factors that were arguably exogenous: the Vietnam War and the baby boom. So it is at least possible that firms shifted resources away from general technological progress in the direction of innovations specifically geared toward the new plentiful supply of college–educated workers. Modelling and empirical investigation of this are beyond the scope of this paper, but could be useful topics for further research.[6]

E. Low Frequency Implications and Evidence

To summarize the results thus far: We find robust evidence of a surge in skilled labor–augmenting technical progress from the early 1970s to the early 1980s, 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, and energy costs. Somewhat surprisingly, we fail to find evidence that capital—whether defined as total plant and equipment, just equipment, or just new plant and/or equipment—plays a significant role.

It is worth pointing out that the presence of skilled labor–augmenting technical progress is not immediately apparent in the MP data. 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 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.

[6] Acemoglu (1997) develops a model along these lines.

To document this we next provide results based on a cross section of industry averages. Table V provides regression results based on

$$T\hat{F}P_i = \hat{A}_i^* + \bar{\alpha}_i^s \hat{A}_t^s + \bar{\alpha}_i^u \hat{A}_t^u + \bar{\alpha}_i^e \hat{A}^e + \bar{\alpha}_i^m \hat{A}^m + \epsilon_i \quad (20)$$

and special cases thereof from the cross–section of 450 industry averages over 1959–1973 and 1974–1991 subsamples, where the "ˆ" refers to the average growth rate of the underlying variable, and the "−" over the shares indicate industry averages over the same period. We take 1973 as the cutoff based on the results embodied in Tables I and IV and Figure II. Both OLS and WLS results are provided under a variety of specifications. The unweighted regression univariate regression 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 $\hat{A}^s$ for the 1974–1991 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. The estimates of $\hat{A}^e$ 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 $\hat{A}_t^s$.

IV. Discussion and Conclusions

This paper has provided evidence of a major structural break in sectoral patterns of productivity growth within manufacturing during the 1970s and 1980s. Specifically, it documents a surge in productivity growth favoring industries with high shares of skilled labor that began around 1972 and continued for approximately ten years. It fails to find evidence of any similar association of TFP growth with capital intensity or with capital investment. These findings thus complement earlier studies of wage and employment patterns that find that the demand for educated or experienced workers rose sharply during roughly the same time period. Provided the elasticity of substitution across factors is greater than one, the interpretation of these patterns in TFP growth as skilled labor–augmenting technical progress is consistent with other findings of an acceleration of skill–biased technical progress during roughly the same time period.

Although part of the motivation of this work is the increased skill premium since the late 1970s, the findings in this paper, while contributing to an overall picture of what happened, cannot by themselves explain the changes in relative wages. First, our study is confined to the manufacturing sector, which represents but one–fifth of the economy. We cannot say whether similar patterns occur in other sectors, and even large increases in the demand for skilled labor in manufacturing will not necessarily have large effects on the overall structure of wages unless the increases are present in other sectors as well. Second, even if manufacturing were representative of the economy, it seems more likely that the findings reflect some combination of sector–biased (that is, Hicks–neutral progress that is correlated with industry skill–intensity) and skilled labor–augmenting technical progress—if only because the effects are too large to be entirely the latter. To the extent the results reflect sector–biased Hicks–neutral technical change, the implications for relative wages would be ambiguous.[7]

To see that the effects are "too large," note that for the economy as a whole, the effect of skilled labor–augmenting technical progress on relative wages can be expressed as (see equation (10)):

$$\hat{W}^s - \hat{W}^u = (1 - 1/\sigma)(\hat{A}^s - \hat{A}^u) - (1/\sigma)(\hat{N}^s - \hat{N}^u), \tag{21}$$

where $\hat{N}^s - \hat{N}^u$ is the change in the relative supplies of skilled and unskilled labor. The regression results from Table IV (which presume no sector–biased technical progress) imply that $\hat{A}^s - \hat{A}^u$ grew at a 45 percent annual rate from 1974–1981. This in itself seems

[7] The effect on the relative wage in this case depends on relative output prices (in a closed or large open economy), which in turn depends on output demand elasticities.

implausibly large, and suggests that these effects in fact do include sector–biased progress. To further translate this into a relative wage effect (still assuming no sector bias), we need to say something about the value of σ, the elasticity of substitution between skilled and unskilled labor. Bound and Johnson [1992] arrive at a value of $\sigma = 1.75$ using disaggregated data. Substituting anything like the estimated values of $\hat{A}^s - \hat{A}^u$ from Table IV, together with historical values for $\hat{N}^s - \hat{N}^u$ (based on BLS aggregate manufacturing employment of production and non–production workers) and $\sigma = 1.75$, leads to implied relative wage growth in excess of 15 percent annually. Even using $\sigma = 1.25$ would imply 7 percent annual growth, which is substantially larger than anything suggested by the studies cited in the introduction.

The onset of skill–related productivity growth in the early 1970s found in this paper also precedes the growth in the skill premium by at least five years, though it does coincde with Greenwood and Yorukoglu's [1996] timing of the "watershed" of 1974 that they argue initiated both the rise in income inequality and the slowdown of aggregate productivity. The decline in the skill premium during the 1970s is attributable to the large increase in the relative supply of skilled (i.e. college–educated) workers at that time. Indeed, some authors (e.g. Autor, Katz, and Kreuger [1997]) have argued that the increase in the demand for skilled labor may have begun in the early 1970s, but was masked by the supply increase.

Greenwood and Yorukoglu's story is that an acceleration of technical progress in information technology (manifesting itself in lower equipment prices) lead to increased demand for skilled labor. They suggest that the new technology requires investment in learning—a task performed only by skilled workers–which causes measured productivity to fall initially. While more work is needed, it is possible that the negative association of new equipment and productivity during this time period reflects such learning. Our findings would then suggest that industries with larger shares of skilled labor can more readily absorb the technology embodied in new equipment and translate it into higher productivity.

TABLE I
Univariate Regression Results with MP Dataset

Year	ΔlnA^s	ΔlnA^*	Year	ΔlnA^s	ΔlnA^*
60	-0.0172	-0.0065	76	-0.0308	0.0308
	(0.0391)	(0.0042)		(0.0322)	(0.0039)
61	0.0960	-0.0065	77	0.1837	0.0019
	(0.0274)	(0.0032)		(0.0298)	(0.0036)
62	-0.0066	0.0282	78	0.1076	-0.0011
	(0.0206)	(0.0025)		(0.0310)	(0.0039)
63	0.0809	0.0180	79	0.2585	-0.0216
	(0.0303)	(0.0037)		(0.0315)	(0.0040)
64	-0.0326	0.0195	80	0.4257	-0.0535
	(0.0150)	(0.0017)		(0.0422)	(0.0058)
65	-0.0191	0.0265	81	0.1221	-0.0130
	(0.0191)	(0.0021)		(0.0355)	(0.0051)
66	0.0858	-0.0077	82	0.0010	-0.0091
	(0.0157)	(0.0019)		(0.0329)	(0.0050)
67	0.0675	-0.0073	83	-0.0337	0.0253
	(0.0260)	(0.0032)		(0.0369)	(0.0058)
68	-0.0514	0.0231	84	-0.0441	0.0295
	(0.0248)	(0.0031)		(0.0370)	(0.0058)
69	0.0766	-0.0065	85	0.0228	0.0085
	(0.0177)	(0.0022)		(0.0317)	(0.0051)
70	-0.0877	-0.0164	86	0.0393	-0.0044
	(0.0255)	(0.0032)		(0.0262)	(0.0044)
71	-0.2568	0.0445	87	0.0305	0.0342
	(0.0279)	(0.0033)		(0.0255)	(0.0042)
72	0.1278	0.0037	88	-0.1114	0.0157
	(0.0397)	(0.0047)		(0.0233)	(0.0039)
73	-0.0121	0.0319	89	-0.0747	0.0059
	(0.0338)	(0.0039)		(0.0184)	(0.0031)
74	0.2341	-0.0306	80	-0.0166	-0.0018
	(0.0458)	(0.0053)		(0.0225)	(0.0038)
75	0.1818	-0.0596	91	0.0531	-0.0173
	(0.0466)	(0.0057)		(0.0236)	(0.0039)

Note: Standard errors are in parentheses. The dependent variable is gross output–based TFP growth. The sample size for each year is 449.

TABLE II

Regression Results, Merged CPS-MP Data

	Skill Definition							
	16 years		14 years		12 years		Non-prod. labor	
Year	$\Delta \ln A^s$	$\Delta \ln A^*$	$\Delta \ln A^s$	$\Delta \ln A^*$	$\Delta \ln A^s$	$\Delta \ln A^*$	$\Delta \ln A^s$	$\Delta \ln A^*$
79	0.601	-0.037	0.434	-0.047	0.135	-0.046	0.388	-0.062
	(0.210)	(0.017)	(0.150)	(0.020)	(0.106)	(0.042)	(0.142)	(0.026)
80	0.817	-0.097	0.576	-0.107	0.141	-0.087	0.704	-0.164
	(0.226)	(0.019)	(0.160)	(0.022)	(0.111)	(0.045)	(0.139)	(0.027)
81	0.173	-0.014	0.059	-0.008	-0.132	0.053	0.092	-0.018
	(0.202)	(0.018)	(0.144)	(0.021)	(0.107)	(0.043)	(0.137)	(0.027)
82	-0.090	-0.011	-0.163	0.005	-0.365	0.130	-0.171	0.016
	(0.187)	(0.019)	(0.139)	(0.022)	(0.112)	(0.047)	(0.139)	(0.030)
83	0.303	0.000	0.248	-0.009	0.042	0.012	-0.121	0.054
	(0.182)	(0.020)	(0.142)	(0.023)	(0.119)	(0.050)	(0.134)	(0.029)
84	0.069	0.040	0.054	0.038	-0.073	0.078	-0.077	0.063
	(0.165)	(0.019)	(0.131)	(0.022)	(0.116)	(0.050)	(0.130)	(0.028)
85	0.168	-0.013	0.130	-0.016	0.087	-0.031	0.182	-0.032
	(0.158)	(0.020)	(0.127)	(0.023)	(0.120)	(0.052)	(0.127)	(0.028)
86	0.053	-0.004	0.006	0.000	-0.081	0.037	0.025	-0.004
	(0.163)	(0.020)	(0.125)	(0.024)	(0.125)	(0.055)	(0.126)	(0.028)
87	-0.020	0.076	-0.038	0.080	-0.208	0.164	-0.114	0.098
	(0.159)	(0.020)	(0.126)	(0.024)	(0.120)	(0.053)	(0.122)	(0.027)
88	0.066	0.013	0.056	0.011	0.108	-0.026	-0.172	0.058
	(0.155)	(0.019)	(0.126)	(0.023)	(0.118)	(0.052)	(0.119)	(0.027)
89	0.038	-0.010	0.026	-0.010	-0.001	-0.005	-0.131	0.023
	(0.152)	(0.020)	(0.121)	(0.024)	(0.118)	(0.053)	(0.118)	(0.027)
90	0.270	-0.036	0.192	-0.038	0.083	-0.039	0.244	-0.055
	(0.137)	(0.019)	(0.110)	(0.023)	(0.116)	(0.053)	(0.120)	(0.028)
91	0.341	-0.058	0.285	-0.070	0.155	-0.084	0.155	-0.049
	(0.150)	(0.021)	(0.129)	(0.026)	(0.126)	(0.057)	(0.127)	(0.029)
	$R^2 = 0.182$		$R^2 = 0.181$		$R^2 = 0.169$		$R^2 = 0.193$	

Note: Standard errors are in parentheses. The dependent variable is value added-based TFP growth. The sample size is 858 (66 observations for 13 years).

TABLE III
Sample Statistics on Measures of
Skilled Labor Share and TFP Growth

	$\alpha(16)$	$\alpha(14)$	$\alpha(12)$	$\alpha(NP)$	TFP growth(%)
Sample Mean	0.107	0.166	0.419	0.201	1.769
Corr. with $\alpha(16)$	1.000	0.984	0.526	0.869	0.238
Corr. with TFP growth	0.238	0.198	-0.033	0.061	1.000

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

TABLE IV

Regression Results, Embodied Capital Improvement

$$\Delta lnTFP_{it} = \Delta lnA_t^* + \alpha_{i,t-1}^s \Delta lnA_t^s + \alpha_{i,t-1}^u \Delta lnA_t^u + \alpha_{i,t-1}^k (I_{i,t-1}/K_{i,t-1})(Z_{t-1}/A_{t-1}^e - 1)$$

Year	ΔlnA^*	ΔlnA^s	ΔlnA^u	$\frac{Z_{t-1}}{A_{t-1}^e} - 1$	Year	ΔlnA^*	ΔlnA^s	ΔlnA^u	$\frac{Z_{t-1}}{A_{t-1}^e} - 1$
60	0.0131	0.0255	-0.1003	-0.3109	76	0.0756	-0.0050	-0.2038	-0.7163
	(0.0078)	(0.0587)	(0.0356)	(0.5039)		(0.0085)	(0.0318)	(0.0338)	(0.3292)
61	-0.0107	0.1005	0.0359	-0.1923	77	0.0140	0.1868	-0.0656	-0.0406
	(0.0069)	(0.0325)	(0.0271)	(0.3757)		(0.0090)	(0.0314)	(0.0338)	(0.3676)
62	0.0435	0.0332	-0.0575	-0.6397	78	0.0313	0.1216	-0.1457	-0.4353
	(0.0052)	(0.0268)	(0.0219)	(0.3037)		(0.0107)	(0.0321)	(0.0379)	(0.3649)
63	0.0346	0.1461	-0.0276	-1.2645	79	0.0470	0.3393	-0.2389	-1.6575
	(0.0080)	(0.0381)	(0.0327)	(0.4737)		(0.0111)	(0.0363)	(0.0395)	(0.3625)
64	0.0163	-0.0506	-0.0047	0.3909	80	0.0346	0.6039	-0.2842	-2.6952
	(0.0042)	(0.0187)	(0.0167)	(0.2228)		(0.0153)	(0.0578)	(0.0544)	(0.5461)
65	0.0273	-0.0231	-0.0253	0.2687	81	0.0426	0.2160	-0.2409	-1.1360
	(0.0054)	(0.0206)	(0.0200)	(0.2656)		(0.0124)	(0.0535)	(0.0470)	(0.4420)
66	-0.0064	0.0868	-0.0003	-0.0737	82	0.0263	0.0253	-0.1677	-0.4257
	(0.0045)	(0.0159)	(0.0172)	(0.1750)		(0.0131)	(0.0510)	(0.0456)	(0.4863)
67	-0.0350	0.0329	0.0802	0.7580	83	0.1343	0.2133	-0.4816	-2.8478
	(0.0077)	(0.0284)	(0.0290)	(0.2759)		(0.0138)	(0.0706)	(0.0532)	(0.6134)
68	0.0696	0.0158	-0.1861	-0.9490	84	0.0709	-0.0537	-0.2262	-0.1117
	(0.0067)	(0.0287)	(0.0279)	(0.2518)		(0.0133)	(0.0782)	(0.0565)	(0.6834)
69	0.0049	0.0735	-0.0725	0.1229	85	0.1220	0.3946	-0.4266	-3.9433
	(0.0047)	(0.0211)	(0.0199)	(0.1959)		(0.0151)	(0.0736)	(0.0557)	(0.6489)
70	-0.0234	-0.1208	-0.0287	0.8422	86	0.0297	0.0452	-0.1714	-0.2483
	(0.0071)	(0.0277)	(0.0289)	(0.2655)		(0.0114)	(0.0464)	(0.0421)	(0.4072)
71	0.0703	-0.2465	-0.1594	0.0873	87	0.0698	0.0062	-0.1957	0.0223
	(0.0069)	(0.0288)	(0.0296)	(0.2581)		(0.0116)	(0.0431)	(0.0402)	(0.4997)
72	-0.0291	0.0624	-0.0124	2.9196	88	0.0357	-0.0333	-0.0108	-1.3638
	(0.0098)	(0.0388)	(0.0418)	(0.3845)		(0.0093)	(0.0286)	(0.0348)	(0.3236)
73	0.0672	0.0061	-0.0538	-1.5884	89	0.0303	-0.0348	-0.0838	-0.8083
	(0.0089)	(0.0318)	(0.0342)	(0.3037)		(0.0076)	(0.0231)	(0.0298)	(0.2388)
74	0.0313	0.2779	-0.2470	-1.1680	90	0.0415	0.0502	-0.1088	-1.5601
	(0.0115)	(0.0440)	(0.0456)	(0.3921)		(0.0092)	(0.0252)	(0.0351)	(0.2512)
75	-0.0206	0.1983	-0.1821	-0.3984	91	0.0571	0.1450	-0.1817	-2.7301
	(0.0130)	(0.0470)	(0.0491)	(0.4252)		(0.0096)	(0.0252)	(0.0356)	(0.2788)

Note: Standard errors are in parentheses. The dependent variable is gross output–based TFP growth. The sample size for each year is 449.

TABLE V
Cross–Section Results

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

1959–73

	$\hat{A}^*$	$\hat{A}^s$	$\hat{A}^u$	$\hat{A}^e$	$\hat{A}^m$	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

	$\hat{A}^*$	$\hat{A}^s$	$\hat{A}^u$	$\hat{A}^e$	$\hat{A}^m$	R^2
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)	

Note: “equip.” or “total” indicates whether capital’s share includes just equipment or equipment plus structures. Standard errors are in parentheses. The dependent variable is average TFP growth over the indicated time period. The sample size for each regression is 449.

Appendix 1: 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

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

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.)

Appendix 2: Additional Details on Data Construction

1. MP Dataset: This is the Bartlesman–Gray dataset version dated July 16, 1996, with data from 1958–1991. Current versions and extensive documentation is available at http://www.nber.org.

a. To compute real equipment investment, we obtained deflators for equipment and structures at the 2–digit level from the Commerce Department's *Fixed Reproducible Tangible Wealth* yearly, and applied them to the corresponding 4–digit industries directly from Wayne Gray.

b. To compute plant and equipment shares, we obtained 4–digit depreciation rates for equipment and capital from Wayne Gray. We added these depreciation rates to a constant $r = 0.4$ to get the $r + \delta_i$ used to compute the shares.

2. CPS Dataset: This is the Outgoing Rotation CD–ROM compiled at the NBER, with data from 1979–91.

a. To construct skilled labor's share in industry i, we selected all workers in the sample from that industry, and within that group selected those who met the skill criterion (e.g. schooling level). Denoting the set of skilled workers by Ψ_i, skilled labor's share in industry i is

$$\alpha_{it}^{s} = \frac{\Sigma_{j\in\Psi_i} UE_{jt}}{\Sigma_{j\in i} UE_{jt}}$$

where UE_{jt} is the "usual weekly earnings of worker j in year t.

b. Education level was determined by the variable "last year of schooling completed."

3. NIPA data:

To adjust the labor share variables for fringe benefits (which are not included in the MP dataset's "earnings" variables, we obtained annual ratios of total labor compensation to wages by 2–digit industry from NIPA Tables 6.2C and 6.3C.

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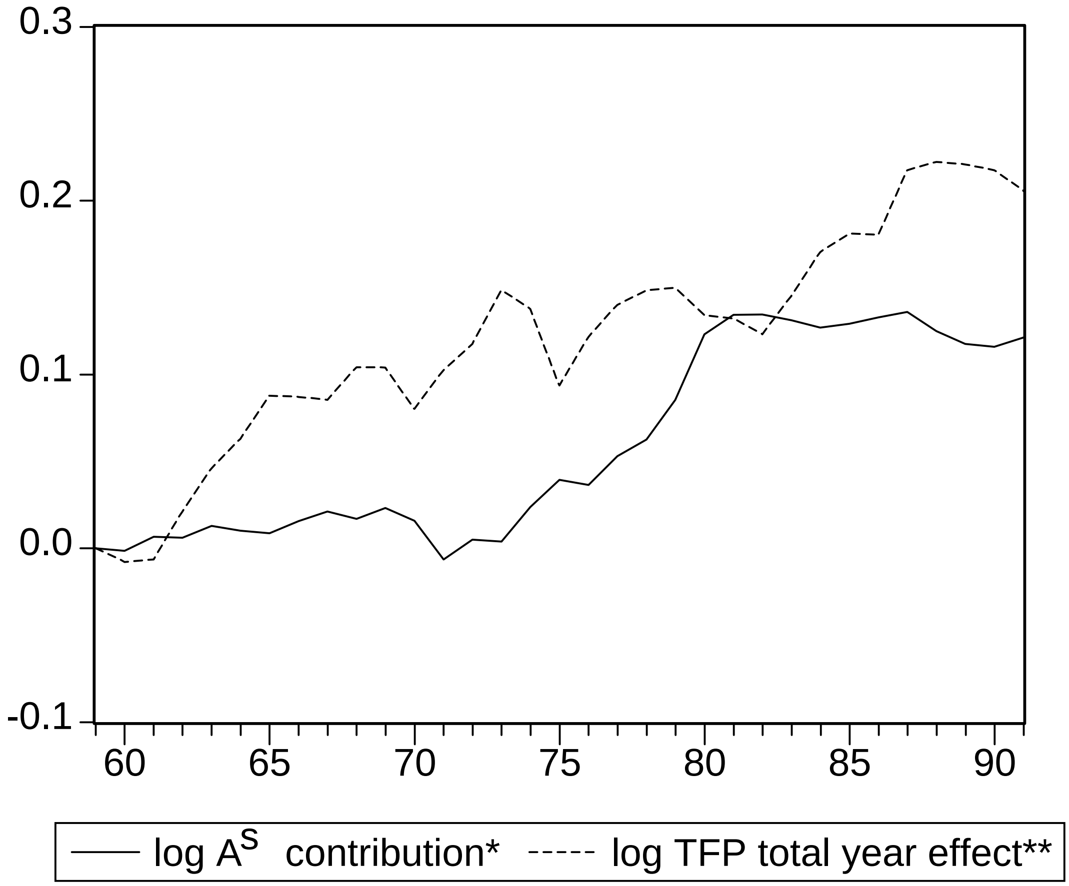
Figure I
Average Gross Output Factor Shares, 1959-1991*

*The averages are computed annually across 449 industries
in the MP data set for each factor share.

Figure II
Contribution of Skilled Labor-Augmenting Technical Progress to TFP
(based on Table I estimates)



*$\log A^S$ multiplied by average skilled labor's share
**$\log A^S$ contribution plus logA*
Both series are normalized to zero in 1959

Figure III
Employment-Weighted TFP Growth versus Skill Share (Selected Years)