THE IMPACT OF OUTSOURCING AND HIGH-TECHNOLOGY CAPITAL ON WAGES: ESTIMATES FOR THE UNITED STATES, 1979-1990*

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Abstract

We estimate the relative influence of trade versus technology on wages in a "large country" setting, where technological change affects product prices. Trade is measured by the foreign outsourcing of intermediate inputs, while technological change is measured by expenditures on high-technology capital such as computers. In our initial specification, we find that computers explain about 35 percent of the increase in the relative wage of nonproduction workers, while outsourcing explains at most 15 percent. In an alternative specification, outsourcing explains about 40 percent of the increase in the relative nonproduction wage, whereas computer expenditures can explain 75 percent of this increase.

I. Introduction

The recent economic performance of less-skilled workers in industrial countries is an important policy topic and the subject of intense academic attention. During the 1980s and 1990s, the wages of low-skilled workers have fallen both in real terms and relative to those of high-skilled workers. The two most widely-cited explanations for the rise in wage inequality are skill-biased technical change and trade with low-wage countries. Of these two, technical change due to the use of computers is often believed to be the dominant explanation.

The goal of this paper is to develop a new methodology and estimate the impact of trade and technology on wages, for the United States over the period 1979-1990. We will measure trade by the foreign outsourcing of intermediate inputs,[1] while we will measure potential technical change by the shift towards high-technology capital such as computers. The starting point for our analysis is a popular method to predict wage changes under zero-profits: a regression of the *change* in industry prices on the *level* of factor cost-shares in that industry, where the estimated coefficients are interpreted as the predicted change in factor-prices that are consistent with the movement in product prices. This "price regression" was first used by Baldwin and Hilton [1984], and more recently by Leamer [1994, 1998], Baldwin and Cain [1997], and Krueger [1997]. In contrast to existing literature, we argue that when fully specified, this regression becomes an *identity* and cannot offer any prediction of the implied changes in factor prices, other than that which actually occurred.

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[1] Foreign outsourcing was first considered by Lawrence and Slaughter [1993] and more recently by Feenstra and Hanson [1996a,1996b]. Lawrence and Slaughter [1993] and Berman, Bound and Griliches [1994] argue that the amount of outsourcing from the U.S. is too small to explain the change in wages, but this was due to the narrow measure of outsourcing that they used [see Feenstra and Hanson, 1996a, pp. 106-107]. We will be using a measure of outsourcing constructed as in Feenstra and Hanson [1996b], which is estimated imports of intermediate inputs into each industry. This measure may also miss aspects of outsourcing, such as the use of computer programmers in India for products otherwise manufactured in the U.S. Leamer [1998] introduces the broader term "delocalization" to indicate the many ways that pieces of the research/production/marketing processes can be moved offshore.

To move beyond this stalemate, we shall modify the conventional price regression using a two-stage estimation procedure. First, we examine how changes in structural variables, such as foreign outsourcing and high-technology capital, affect industry prices and productivity. By treating industry prices (and productivity) as endogenous, we allow for a large-open-economy setting. From these first-stage results, we decompose price and productivity changes into portions that are attributable to each structural variable. Second, using a modified version of the price regression, we use the decomposed price and productivity changes from the first stage to estimate the change in primary factor prices that is attributable to each structural variable separately. The results indicate how much of the observed rise in wage inequality is attributable to foreign outsourcing or high-technology capital. While we focus on these two explanations, the methodology we develop is quite general and could be used to examine the relationship between factor prices and many types of changes in production techniques.

Our approach may help resolve an apparent conflict in the literature over whether it is the factor bias or the sector bias of technological changes that matters for wages.[2] Krugman [1995] and Leamer [1998] have debated this point, with Krugman arguing that factor bias is important in a closed or large open economy, and Leamer arguing that sector bias is all that matters in a small open economy (or even with log-linear pass-through from productivity to prices). To resolve this, we need to have a indication of which setting is empirically relevant. This will turn out to be a byproduct of our analysis, since our first-stage regression can distinguish between sector-biased and factor-biased technological changes: *both* of these changes affect industry prices, but (with Cobb-Douglas preferences) only the factor-biased changes will have an impact on wages and prices *over and above* their impact on productivity. Thus, in a regression of industry prices on total factor productivity, a test for the presence of additional structural variables can be interpreted as a test for non-neutral technological change (conditional on finding complete pass-through from productivity to prices).

The specification of our model is derived in sections II and III, while the data are discussed in section IV and empirical results are presented in section V. In our empirical results, we begin by examining the impact of foreign outsourcing and alternative measures of high-technology capital on the relative demand for skilled labor. This allows comparison with existing literature and our later results. We then consider two specifications to explain industry changes in prices and productivity. In the first, we assume that the structural variables enter linearly as independent variables. In that case we find that computers explain about 35 percent of the increase in the relative wage of nonproduction workers, while outsourcing explains at most 15 percent. In the second specification, we allow for interactions between the structural variables and quantities of primary factors. We then find that foreign outsourcing explains about 40 percent of the increase in the relative nonproduction wage, whereas computer expenditures can explain 75 percent of this increase. Our conclusions are discussed further in section VI.

II. Price Regression

The first step in our empirical specification is derive the "price regression" that has been used by Baldwin and Hilton [1984], Leamer [1994, 1998], Baldwin and Cain [1997] and Krueger [1997]. The typical method to derive the relation between changes in prices, productivity, and wages is to totally differentiate the zero-profit condition for each industry. This yields a system of equations with the change in commodity prices on the left, the change in industry wages

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[2] See Haskel and Slaughter (1998) and Kahn and Lim (1998) for evidence on the sector-bias of technical change and Berman, Bound, and Machin (1997) for international evidence on skill-biased technical change.

weighted by each factor cost share on the right, and productivity also appearing on the right with a negative sign (since a rise in productivity can lower prices). Expressing this in first-differences, we have

(1) $$\Delta \ln p_{it}^{VA} = -TFP_{it} + \tfrac{1}{2}(s_{it-1} + s_{it})' \Delta \ln w_{it} ,$$

where p_{it}^{VA} denotes the value-added price in industry i=1,…,N, TFP_{it} denotes total factor productivity, w_{it} denotes the vector of primary factor prices in industry i, and s_{it-1} and s_{it} are the primary factor cost-shares that are averaged over the two periods.[3,4]

Regardless of the theoretical derivation of (1), its ability to hold in the data will depend on the measure of total factor productivity that is used. In particular, the *dual* Tornqvist index of TFP [Caves, Christensen and Diewert 1982a,1982b] is defined as the difference between the log change in industry prices, and the cost-shared weighted change in factor prices. Using this particular measure of productivity, (1) clearly holds as an *identity*, as we assume. It is perhaps more common to work with the primal Tornqvist index of TFP, which equals the log change of output minus the share-weighted growth of inputs. While the primal and dual measures are not equal in general, their difference is extremely small in our sample.[5]

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[3] The value-added price is constructed as $\Delta \ln p_{it}^{VA} \equiv [\Delta \ln p_{it} - \tfrac{1}{2}(r_{it-1} + r_{it})' \Delta \ln p_t] / [\sum_{j=1}^{N} \tfrac{1}{2}(r_{ijt-1} + r_{jit})]$, where r_{ijt} is the cost share of intermediate input j used in the production of industry i=1,…,N.

[4] We impose the assumption of perfect competition, so that revenue equals costs, and the cost-shares are measured by the revenue shares. Hall [1988] and Domowitz, Hubbard, and Petersen [1988] suggest that imperfect competition may bias standard measures of total factor productivity and that one should account for this bias by introducing controls for price-marginal cost markups. In our empirical analysis, we find that introducing such controls (output-capital ratios) has little effect on parameter estimates.

[5] The primal measure of TFP is defined as the growth of value-added minus the weighted average growth of primary factors. It has a correlation of 0.999 with the dual measure of TFP defined by (2), for 1979-1990.

In order to move from equation (1) to the price regression, as it is conventionally applied, we treat $\Delta \ln w_{it}$ as a random variable over industries i and denote its mean value by ω_t. Then using this notation in (1), we readily obtain

(2) $$\Delta \ln p_{it}^{VA} = -\,TFP_{it} + \tfrac{1}{2}(s_{it-1} + s_{it})'\omega_t + e_{it} \ ,$$

where the final term appearing on the right is

(3) $$e_{it} \equiv \tfrac{1}{2}(s_{it-1} + s_{it})'(\Delta \ln w_{it} - \omega_t) \, .$$

This term equals the average deviation of industry-specific factor-price changes from their mean levels. We refer to the magnitude in (3) as the “change in wage differentials,” since it reflects the change in the industry-specific wages for labor (and rental price of capital) in relation to their manufacturing-wide levels. This term is usually excluded from estimation of the price regression and hence implicitly treated as an error term. The change in wage differentials can be measured with available data, however, and we shall explicitly account for its presence in our work.

There are two general sources of variation in factor prices across industries, leading to inter-industry wage differentials: unobserved variation in factor quality and industry-specific rents. There is extensive empirical literature on inter-industry differences in wages, much of which is devoted to ascertaining their source [e.g., Krueger and Summers 1988, Murphy and Topel 1990, Gibbons and Katz 1992]. Since we examine long-run changes in factor prices in an environment where factors are assumed to be perfectly mobile across industries, we prefer to interpret inter-industry factor-price variation as resulting from variation in *factor quality* across industries, which is consistent with the neoclassical trade model that is the foundation for our analysis. Under this assumption, the effective wages paid by industries – after accounting for quality differences – are properly measured by the manufacturing-wide wages, or ω_t. It follows that the *effective total factor productivity* is measured by:

$$\text{ETFP}_{it} \equiv \text{TFP}_{it} - e_{it} \; . \tag{4}$$

Combining (4) and (2), we obtain an alternative version of the price regression that incorporates the inter-industry wage differentials:

$$\Delta \ln p_{it}^{VA} = -\,\text{ETFP}_{it} + \tfrac{1}{2}(s_{it-1} + s_{it})'\omega_t \; . \tag{2'}$$

What is exceptional about the price regression in (2') is that by *including* the change in wage differentials as a variable in (2), the regression will fit exactly because it is an identity. In Table 1, we report results from estimating (2') using data from the NBER Productivity Database (Bartelsman and Gray, 1996), which contains the value of industry prices, shipments, input usage, and factor prices for four-digit SIC manufacturing industries over the period 1958-1991. There are 450 four-digit SIC industries in the United States. We exclude three industries (SIC 2067, 2794, 3483) due to missing data on materials purchases or prices.[6] The value-added price is constructed as a log-difference over the period 1979-1990, divided by the number of years in each period to obtain an annualized difference. We use the primal measure of TFP, expressed as an annualized difference. The other independent variables are the average cost-shares (over the first and last year for the period) for production labor, non-production labor, and

[6] There are data on aggregate material purchases for some of these industries, but not on detailed material purchases from individual industries, which we would need in order to construct an estimate of imported intermediate inputs. Since we are forced to exclude these industries in later regressions in which we use foreign outsourcing as an independent variable, for sake of consistency we also exclude them from the regressions in Table 1.

capital. The mean values for these and other variables are shown in Table 2.

The regression shown in the first column of Table 1 includes effective TFP and the average factor-shares. The estimated coefficients can be compared to the annual average changes in the prices of production labor, non-production labor, and capital for 1979-1990 shown at the top of Table 2. The estimated coefficients are extremely close to the actual factor price changes reported in Table 2, and the regression fits nearly perfectly (when we replace effective TFP constructed from the primal with effective TFP constructed from the dual, the regression fits exactly). The wage of nonproduction labor rises faster than that of production labor, indicating an increase in wage inequality during the 1980s.

In order to compare this near-identity to the price regression as it appears in the literature, it is useful to consider another version of (2') where we explicitly introduce the prices of intermediate inputs on the right-hand side, rather than incorporating them into the value-added prices on the left. Leamer [1998] includes the materials term on the left, while constraining its coefficient at unity, while Krueger [1997] allows the coefficient to be estimated. We will experiment with both approaches, though our results do not exactly reproduce those of Leamer or Krueger due to differences in the sample and other features.[7] In the second column of Table 1, we introduce the materials cost share multiplied by its log-change in price over 1979-1990, and similarly for energy, as independent variables. In addition, all variables in the regression are re-weighted so that the cost shares over *all factors* sum to unity (as contrasted to regression (1), where the cost shares over just the primary factors sum to unity). This re-weighting has no effect

[7] In order for (2') to fit as an identity, the capital share that is used must be constructed as a residual, by subtracting the payments to all other factors from the value of shipments. This means that the price of capital being used is the *ex post* rate of return. In contrast, Leamer [1998] constructs a capital share using an assumed uniform rate of return on capital across all industries.

on an identity, of course, and regression (2) continues to fit nearly perfectly. The re-weighting does have an impact on the rest of the results in Table 1.

In regression (3), we replace effective TFP with primal TFP, so that the change in wage differentials is effectively *excluded* from the price regression, while keeping the coefficients on materials and energy at unity (following Leamer [1998]). In this case the coefficients obtained suggest that the wage of production labor rose faster than nonproduction labor over the period 1979-1990, or that wage inequality *decreased*. This result indicates that the omitted variable – the change in wage differentials – is positively correlated with the production labor cost-share (it is also positively correlated with the capital share). Alternatively, in regression (4) we omit the computer industry (SIC 3573) from the sample (following Sachs and Shatz [1994]). In this case the original pattern of wage coefficients is restored, showing that wage inequality *increased.* Finally, in regression (5) we also drop TFP as a regressor, while estimating the coefficients on materials and energy (following Krueger [1997]). Then the coefficient estimates showing rising wage inequality are preserved, though the magnitude of the effect is exaggerated.

The point of Table 1 is to show that estimates from the conventional price regression are extremely sensitive to its exact specification (particularly what measure of TFP to include), but that when it is *fully specified* (using effective TFP) it becomes an identity. The results obtained when some variable is omitted depend, in the standard way, on the correlation between the omitted and included variables, and this is the only reason for the coefficients obtained to not equal the observed change in wages. This leads to the obvious question of whether the price regression should be used at all to infer wage changes. We believe that such inference can still be made, by modifying the price regression as discussed in the next section.

III. Endogenizing Prices and Productivity

The price regression in (2') summarizes how changes in value-added prices and productivity, mediated by factor intensities (the average factor cost shares), influence primary factor prices. We propose to examine how changes in a series of structural variables, such as foreign outsourcing and the purchase of high-technology capital, influence value-added prices and effective productivity, and then, using (2'), examine how the changes in value-added prices and productivity implied by the structural variables influence factor prices. Thus, our methodology has two stages. First, we regress changes in effective productivity and value-added prices on the structural variables. Second, using the first-stage estimation results and the price regression, we decompose changes in primary factor prices into portions that are attributable to each structural variable. We begin by describing the mechanics of the estimation and then, building on trade and production theory, provide a conceptual foundation for our regressions.

The impact of structural variables on effective productivity is modeled as

$$ETFP_{it} = \alpha' \Delta z_{it} + \varepsilon_{it} \ , \tag{5}$$

where z_{it} is a (Kx1) vector of structural variables, α is a (Kx1) vector of coefficients, and ε_{it} is a disturbance term that captures all other shocks to productivity, which is assumed orthogonal to z_{it}. Krugman [1995] argues persuasively that changes in productivity are "passed-through" to industry prices, either because the country in question is large in world markets or because the technology shocks are common across countries. Then the changes in effective productivity has a further impact on prices as modeled by

$$\Delta \ln p_{it}^{VA} = \lambda\, ETFP_{it} + \beta' \Delta z_{it} + v_{it} \ , \tag{6}$$

where λ is the pass-through coefficient (we expect $\lambda \leq 0$), β is a (Kx1) vector of coefficients, and v_{it} is another error term. It is significant that in (6) we allow the structural variables z_{it} to have an *direct* impact β on prices, over and above the *indirect* impact via productivity. The need to include this direct impact will be explained below.

Combining (5) and (6), the total impact of the structural variables on value-added prices and productivity in a large-country setting, can be summarized by the following regression:

(7) $$\Delta \ln p_{it}^{VA} + ETFP_{it} = \gamma' \Delta z_{it} + \eta_{it} \ ,$$

where $\gamma_t = (1+\lambda)\alpha + \beta,$ and $\eta_{it} = (1+\lambda)\varepsilon_{it} + v_{it}$. We will regard (6) as a first-stage regression, which allows us to decompose the total change in value-added prices and effective TFP into those components due to each structural variable, namely $\gamma_k \Delta z_{tk}$, where γ_k is the kth element of γ and Δz_{tk} is the kth element of Δz_t.

As a second-stage, we regress this *component* of the change in price and productivity on the factor-shares, thereby obtaining a predicted wage change due to that structural component. The second-stage regressions for each structural variable k are

(8) $$\gamma_k \Delta z_{tk} = \delta_k' (s_{it-1} + s_{it})/2 + u_{kt} \ .$$

The coefficients δ_k obtained from these regressions are interpreted as the change in primary factor prices that are explained by structural variable k. In other words, the regression coefficients in (8) can be seen as the changes in primary factor prices that would have occurred had changes in structural variable k been the only source of changes in value-added prices and productivity. Thus, (8) is a modified version of the price regression in (2'), in which we attempt to estimate the contribution of each structural variable to the average change in primary factor prices. We perform the regression for each structural variable separately.

This essentially completes the description of our methodology, but we should provide further justification for the use of high-technology capital and outsourcing as structural variables. The idea that high-technology capital impacts productivity is the subject of a large literature [e.g., Berndt and Morrison 1995, Morrison 1996, Siegel 1997]. Similar to that literature, what we have in mind is not the contribution of these equipment purchases to the overall capital stock, but to changes in actual production techniques. Doms, Dunne, and Troske [1997] examine the correlation between the usage of automation technologies and the structure of employment and wages at the plant level, which is a direct treatment of how the adoption of new innovations influences production techniques. They focus on whether automation techniques have a *non-neutral* effect on relative demand for production and non-production workers. Our approach is at a more aggregate level, using industry measures of expenditure on computers and other technology-intensive equipment, but we also expect that high-technology capital may contribute to a non-neutral shift in productivity.

It is less obvious that foreign (or domestic) outsourcing should also have an impact on measured productivity, though this is implied by the model developed in Feenstra and Hanson [1996a, 1997]. There we consider a good produced in multiple stages of production. These different stages need not take place in a single country, and of course, the more unskilled-labor intensive stages will be done in the country with lower relative wages for unskilled labor: the transfer of these activities abroad is what we call foreign outsourcing. The activities remaining at home can be aggregated into a production function. With a change in underlying parameters (such as factor endowments at home or abroad, or trade policies), the range of activities done abroad can change. The outsourced activities can be thought of as new intermediate inputs, which will shift the entire production function for activities done at home, and therefore show up in the industry aggregate production function as a change in total factor productivity.[8] This will generally be a non-neutral shift, as outsourcing often takes the form of moving unskilled activities to low-wage countries, thus increasing the relative demand for skilled labor at home.

The presence of non-neutral technological progress implies that the structural variables must enter *directly* into equation (6), in addition to their indirect impact via productivity. This can be understood as follows. Suppose that technology shocks are common across countries, so that we can treat the determination of factor prices as in a closed economy [Krugman, 1995]. Further assume that preferences are Cobb-Douglas. The initial equilibrium is illustrated by point A in Figure 1, where we illustrate the zero-profit conditions $p_i=c_i(w,r)$ in two industries i=1,2, where w denotes the wage of unskilled labor and r denotes the wage of skilled labor. The relative demand for unskilled labor is given by the slope of each iso-cost curve, so the diagram shows the case where industry 1 is skilled-labor intensive.

Initially, consider the case of *neutral* technological progress in industry 1. This is illustrated by the outward shift of the iso-cost line in industry 1 to $p_1=c_1'(w,r)$. In the absence of any change in product prices, the wages would now be determined at point B, where there has

[8] If we observed the full range of activities that constitute production, we could account for outsourcing directly by examining the process through which production stages are divided across countries. Manufacturing data, however, are typically aggregated over production activities at the industry (or sectoral) level. Thus, the effects of outsourcing can only be observed through their effects on average factor intensities in an industry. When outsourcing raises the average skill intensity of production in U.S. industries, its effects mimic those of industry-specific, skill-biased technological change. For this reason, outsourcing and the adoption of new technologies may have observationally equivalent effects on total factor productivity.

been an increase in the relative wage of skilled labor. There would also be an increase in the output y_1, by exactly the amount of the neutral technological progress. With Cobb-Douglas preferences, this would imply an equal and offsetting drop in p_1, which means that the iso-cost line for industry 1 would shift *back* to its original location, and the factor prices would again be determined at point A. This illustrates the general result that with Cobb-Douglas preferences, the determination of factor prices is *independent* of any Hicks neutral progress in either industry [Krugman, 1995]. In terms of equation (6), we would have $\lambda=-1$ as prices move in an equal and offsetting manner with neutral technological progress, and since there is no further change in prices, then $\beta=0$.

We contrast this result with the case of skill-biased technological progress, shown in Figure 2. This would shift the iso-cost line for industry 1 out in a clockwise fashion, to $p_1 = c_1^{'}(w, r)$. Continuing to assume Cobb-Douglas preferences, suppose that p_1 drops in an equal and offsetting fashion, so that the iso-cost line shifts back inwards (equi-proportionally) to the *dashed* line through the point A. In the absence of any factor movement between the industries, the output y_2 would be unaffected and the output y_1 would increase be the same percentage that p_1 has decreased. This means that the goods market is in equilibrium. However, the factor markets are definitely *not* in equilibrium, because there has been an increase in the relative demand for skilled labor in industry 1 (and no change in this demand within industry 2). This will lead to an increase in the relative wage of skilled labor, and therefore, an increase in the relative price of good 1. As a result, there will be a further shifting of the iso-cost lines for both goods (e.g., the iso-cost line for good 1 will shift outwards and that for good 2 will shift inwards), and the equilibrium will be established at a position such as C.[9] The crucial point to recognize is that even for a closed economy with Cobb-Douglas preferences and λ=-1 in eq. (6), there will be a *further feedback effect of the non-neutral progress on the goods prices*, so that $\beta \neq 0$ in (6).[10]

Our arguments above provides a rationale for the structural variables to linearly affect productivity in (5), and to have a *further* impact on value-added prices in equation (6) when the technological change is non-neutral. Empirically, if we find λ=-1 and $\beta \neq 0$ then we can interpret this as evidence that the technological progress is non-neutral. It can be noted here that the presence of additional structural variables in (6) (i.e. $\beta \neq 0$) is precisely how our framework differs from Leamer [1998], who allowed for the pass-through of productivity to prices (i.e. $\lambda \neq 0$), but *did not* allow for other structural variables to affect prices. Leamer argues that even with pass-through from productivity to prices, only the *sectoral* impact of technological change is important. This result relies on his assumption that the pass-through relation between productivity and prices *does not* include any direct impact of structural variables on prices. As we have argued, in order to incorporate *non-neutral* technological shifts, then the additional structural regressors must be included in (6).

A further way to check for evidence of non-neutral technological change would be to include *interaction terms* between the structural variables and the quantities of primary factors, within equations (5)-(7). The coefficients on these interaction terms can be interpreted as the

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[9] The complete set of relations between non-neutral progress parameters and relative factor prices, depending on the elasticities of substitution in demand and in production, has been worked out by Xu (1998). Unfortunately, there does not appear to be a convenient closed-form solution to show how the change in product prices in (6) depend on the non-neutral progress parameters.

[10] This effect will only be enhanced when considering technological shocks across countries. For example, outsourcing could plausibly be correlated with changes in world prices even beyond its impact on TFP in the domestic industry, meaning that this variable should appear independently in the price equation (6).

impact of each structural variable on the relative demand for that primary factor.[11] This suggests that the first stage regression (7) could be re-specified as

$$(7') \qquad \Delta \ln p_{it}^{VA} + ETFP_{it} = \gamma' \Delta z_{it} + \tfrac{1}{2} \Delta z_{it}' A' (\ln x_{it-1} + \ln x_{it}) + \varepsilon_{it},$$

where A is an (MxK) matrix of coefficients to be estimated.

We could then use the estimated coefficients from the first-stage regression (7') to decompose the change in value-added prices plus productivity into the portions attributable to each structural variable k, namely, $\gamma_k \Delta z_{ikt} + \frac{1}{2} \Delta z_{ikt} A_k' (\ln x_{it-1} + \ln x_{it})$, where γ_k is the kth element of γ and A_k is the kth column of A. Finally, we replace the dependent variable in (8) with these magnitudes, and perform the second-stage regression

$$(8') \qquad \gamma_k \Delta z_{ikt} + \tfrac{1}{2} \Delta z_{ikt} A_k' (\ln x_{it-1} + \ln x_{it}) = \delta_k' (s_{it-t} + s_{it})/2 + u_{ikt}.$$

We again interpret the regression coefficients δ_k from this second-stage regression as the estimated changes in factor prices that are attributable to each structural variable k.

IV. Data and Preliminary Regressions

We shall apply the estimation technique described in equations (7) and (8), or (7') and (8'), to U.S. manufacturing industries for the period 1979-1990, which corresponds to the most recent period between business cycle peaks in the U.S. economy. The data we use are from the NBER Productivity Database [Bartelsman and Gray, 1996], as summarized in Table I. The

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[11] In an earlier draft of the paper, we showed how interaction terms of this type could be derived from a translog production function with non-neutral technological progress, and that the coefficients on the interaction terms could be given this interpretation. These results are available on request.

quantity of capital is constructed by Bartelsman and Gray from real investment in assets types, using a perpetual inventory method. We then calculate the price of capital by dividing the payments to capital in each industry (which equals value of shipments less payments to labor and materials) by the quantity of capital; this yields the *ex post* rental price of capital. There are 450 four-digit SIC industries in the United States; we exclude three industries (SIC 2067, 2794, 3483) due to missing data on materials purchases needed to estimate foreign outsourcing.

Movements in labor earnings and factor cost shares in Table I illustrate the rise in wage inequality that occurred during the 1980s. We also show data for 1972-1979, the previous interval between business cycle peaks, to provide a basis of comparison. During the period 1979-1990, the wages of nonproduction workers increased by 5.44 percent per year, while the wages of production workers increased by only 4.71 percent, so that the wages of nonproduction relative to production workers rose by an average of 0.72 percent per year.[12] Partly as a result of these wage movements, the share of production wages in total shipments declined over the two decades (falling from 12.6 percent to 10.3 percent), while the share of nonproduction wages in total shipments remained nearly constant. Looking at other factor prices, the dramatic increase in energy prices during the 1970s contributed to an increase in the share of energy in total costs, which was reversed during the 1980s as energy prices declined in relative terms.

The rise in total factor productivity from the 1970s to the 1980s is apparent in the lower portion of Table I. Also shown are the changes in the exogenous regressors that form the z_{it} vector. The structural changes that we identify are the extent of foreign outsourcing, measured as

[12] The increase in the wage of nonproduction workers relative to the wage of production workers as reported in the Annual Survey of Manufactures is only a small part of the total increase in wage inequality between more and less skilled workers that occurred during the 1980s. See Katz and Murphy [1992] for a discussion. While there are problems with using the production/nonproduction classification as a proxy for skill [Leamer, 1994], there is

the share of imported intermediate inputs in total costs and the share of high-technology capital in the total capital stock. For each variable we will consider several different versions. To measure foreign outsourcing, we combine data on imports of final goods with data on total input purchases. Feenstra [1996, 1997] provides data on total U.S. imports and exports by four-digit SIC manufacturing industry for the period 1972-1994.[13] We combine the trade data with data on material purchases from the *Census of Manufactures*. The *Census* data, which are the raw data used to construct input-output tables, show the value of intermediate inputs that each four-digit manufacturing industry purchased from every other manufacturing industry. For each industry i, we measure imported intermediate inputs as

$$\sum_j \left[\text{input purchases of good j by industry i}\right] * \left[\frac{\text{imports of good j}}{\text{consumption of good j}}\right], \qquad (9)$$

where (apparent) consumption of good j is measured as shipments+imports-exports. Expressing imported intermediate inputs relative to total expenditure on non-energy intermediates in each industry, we obtain the first, *broad* measure of foreign outsourcing. When averaged over all industries, this variable increased from 5.3 percent in 1972 to 7.3 percent in 1979 and 12.1 percent in 1990.

A second measure of outsourcing is obtained by restricting attention to those inputs that are purchased from the same two-digit SIC industry as the good being produced. The idea behind this measure is that foreign outsourcing represents the transfer overseas of production activities that could have been done by that company within the United States. We do not

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evidence suggesting that in practice the classification shows similar trends as using skill categories [Berman, Bound and Griliches, 1994; Sachs and Shatz, 1994].

[13] The import and export data are available from Robert Feenstra over the Internet at www.nber.org.

normally think of, say, the import of steel by a U.S. automobile producer as outsourcing. But it is common to consider the purchase of automobile parts by that company as outsourcing, especially if the parts were formerly made by the same company, or at least purchased in the United States. This idea is captured by restricting the four-digit industry subscripts i and j in (9) to be within the same two-digit SIC industry. The resulting measure of imported intermediate inputs is again expressed relative to total expenditure on non-energy intermediates in each industry, to obtain the second, *narrow* measure of outsourcing. When averaged, this variable increased from 2.2 percent in 1972 to 3.1 percent in 1979 and 5.7 percent in 1990.

Also reported in Table I is the *difference* between the broad and narrow measures of outsourcing, which represents the intermediate inputs from outside the two-digit purchasing industry that are sourced from abroad. Since we feel that the narrow measure -- from within the same two-digit industry -- best captures the idea of outsourcing, we will often enter the narrow measure and the difference between the broad and narrow as separate variables.

The data we use for high-technology capital are from the Bureau of Labor Statistics (BLS) and have been used by Berndt and Morrison [1995] and Morrison [1997].[14] These data distinguish capital by asset type for two-digit SIC manufacturing industries. The BLS first calculates real investment by asset type in each industry in each year by deflating industry asset purchases (e.g., expenditures on office equipment) by the relevant price index (e.g., the producer price index for office equipment). It then applies a perpetual inventory method to calculate the "productive stock" of each asset type in each industry in each year. *Ex post* rental prices for each asset are calculated as in Hall and Jorgenson (1967), and reflect the internal rate of return in each industry and capital gains on each asset. By summing the *ex post* rental prices times the productive stocks of all assets, we obtain the total payments to capital in each industry (equal to value of shipments less payments to labor and materials).

An alternative to the BLS measure of *ex post* rental prices is an *ex ante* measure of rental prices used by Berndt and Morrison, which reflects a "safe" rate of return (the Moody rate of Baa bonds) and excludes capital gains on each asset.[15] Summing the *ex ante* rental prices times the productive stocks of all assets does not yield the observed payments to capital in each industry. Nevertheless, the *ex ante* rental prices might be preferred precisely because they do not reflect capital gains on the assets nor the internal rate of return in the industry.

Berndt and Morrison define high-technology capital to include office, computing and accounting machinery; communications equipment; science and engineering instruments; and photocopy and related equipment. The share of this equipment in total capital gives us the variable denoted by the *high-tech share*. To calculate the share, we take the ratio of the capital stocks multiplied by the *ex post* rental prices, which gives a measure of the share of capital services attributable to high-technology equipment, as shown in Table I. This broad measure increases from 7.3 percent in 1972 to 8.3 percent in 1979, and 12.2 percent in 1990. It can also be measured more narrowly to include only the share of office, computing and accounting machinery in the capital stock, which gives us the *computer share*. This variable is 5.2 percent of capital services in 1972 and 4.2 percent in 1979, and then increases to 6.5 percent in 1990. We will also make use of the *difference* between the high-tech share and the computer share,

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[14] These data are used by the BLS in their multifactor productivity calculations , as discussed in Harper, Berndt and Wood [1989]. We thank Catherine Morrison and Don Siegel for providing us with these data.
[15] The ex ante rental prices we use are the same as those used by Berndt and Morrison [1995] and Morrison [1997]. The formula for these rental prices is given by eq. (29) in Harper, Berndt, and Wood [1989], where the Moody rate for Baa bonds is used to measure the ex ante interest rate and the capital gains term is excluded.

which represents the fraction of capital services derived from various high-technology assets *other than* office, computing and accounting machinery.

As an alternative to using *ex post* rental prices to calculate the services of computers and other high-technology capital, we consider using *ex ante* rental prices. By this measure, the share of high-technology capital in capital services is 5.0 percent in 1972, 5.9 percent in 1979, and 8.6 percent in 1990, while the share of computers in capital services is 3.2 percent in 1972, 2.9 percent in 1979, and 3.6 percent in 1990. Evidently, the computer share calculated with *ex ante* rental prices increases much less over 1979-90 than does the computer share calculated with *ex post* rental prices.

A third measure of computer expenditures can be taken from the *Census,* which asked firms to report what fraction of investment was devoted to computer purchases in 1977, 1982 and 1987. This variable has been used by Berman, Bound and Griliches [1994] and also by Autor, Katz and Krueger [1998].[16] The numerator and denominator of this variable are both investment flows, making the ratio difficult to interpret. We will make use of this variable in our sensitivity analysis, as an alternative to the BLS computer share.

Before applying our two-stage estimation procedure, we report in Table II regressions of the share of the total industry wage bill going to nonproduction workers on the structural variables and some control variables. This regression is very similar to that used by Berman, Bound and Griliches [1994], Autor, Katz and Krueger [1998], and Feenstra and Hanson [1996a], and allows a direct comparison with those papers. The regressions are run cross-sectionally over the four-digit SIC industries, and include changes in the shipments of each industry and the

[16] We thank Larry Katz for providing us with this variable.

capital/shipments ratio as controls. The outsourcing variables and the computer and high-tech shares (but not the *Census* computer investment share) are all measured as annual changes.

In column (1) of Table II, we report the mean values of the dependent and independent variables for 1979-1990. Since these means are weighted by the industry share of the total manufacturing wage bill, they differ somewhat from those reported in Table I. Following this, we report the regression coefficients in columns (2)-(4), where each regression uses alternative measures of the computer and high-technology variables. In all the regressions, we see that the narrow definition of outsourcing has a positive impact on the nonproduction share of the wage bill, as does the computer share and computer investment share. Remaining outsourcing occurring outside of the same two-digit industry has a positive, though smaller, impact on the nonproduction wage share, while the remaining expenditures on high-technology capital are small and insignificant (and in one case negative).

By multiplying the regression coefficients by the mean values for the change in each variable, we obtain the contributions shown in column (5). Of the total annual average change in the nonproduction wage share of 0.39 percent, these contributions show the percentage of that shift due to each of the independent variables. We see that total outsourcing (the narrow measure and the difference) accounts for 13-23 percent of the shift towards nonproduction labor, which is in line with other estimates using slightly different data.[17] The results for computers differ quite dramatically across the specifications. Using capital services at *ex post* rental prices means that computers plus other expenditures on high-technology capital account for 13 percent of the shift towards nonproduction labor; using capital services at *ex ante* rental prices means that that these variables can explain only 8 percent of this shift; and using the computer investment share and the high-technology capital share means that these variables can account for 32 percent of this shift. We will be interested in comparing these results (qualitatively) to what is obtained when we estimate factor-prices change attributable to the different structural variables.

V. Estimation Results

The estimation procedure we develop has two stages. First, we estimate the impact of structural variables such as foreign outsourcing, computers, and other high-technology capital on changes in value-added prices plus effective productivity, using either the linear specification in (7) or the specification with interaction terms in (7'). We then use the estimated coefficients from this first-stage regression to calculate the portion of changes in value-added prices plus productivity that is attributable to each structural variable. Second, we separately regress each of these components on average factor shares, as in (8) or (8'), to obtain estimates of the changes in factor prices that are attributable to each structural variable. The estimation is performed by pooling over the 450 U.S. manufacturing industries at the four-digit SIC level for the periods 1979-1990, excluding the three industries (SIC 2067, 2794, 3483) for which detailed materials data needed to construct outsourcing are unavailable. All variables are constructed as differences or averages within this period.

The first-stage regression of value-added prices plus effective TFP on the structural variables is a reduced form, which combines equations (5) and (6). This specification imposes the assumption that the structural variables affect value-added prices over and above their impact on TFP. To justify our approach, we first regress valued-added prices on effective TFP and the structural variables. The structural variables are jointly statistically significant (at the 1% level)

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[17] See Feenstra and Hanson [1996b] and the "Errata" to those results, available on request.

in this regression, which, following the discussion in section III, suggests that the structural variables contribute to non-neutral shifts in technology. The estimated pass-through coefficient of effective TFP to value-added prices (λ in equation (6)) is –1.01 (standard error of 0.01).[18] It is difficult to interpret this coefficient, however, since effective TFP is certainly correlated with value-added prices by its construction (see (2)), making the OLS estimate biased towards -1. In principle, one could use instrumental variables to obtain consistent estimates of the pass-through coefficient, but the best candidate instruments we have for TFP are the structural variables, which are invalid given that they are correlated with value-added prices, independent of their correlation with effective TFP.[19] Thus, we cannot improve upon the OLS estimate of –1.01 between productivity and prices, though we can conclude that the structural variables enter this relation independently. As argued in section III, the appearance of these structural variable can be interpreted as evidence of non-neutral technological progress (conditional on the pass-through coefficient being –1). The fact that we are not able to obtain a consistent estimate of the pass-through coefficient does not hinder our analysis, since by summing (5) and (6), we can estimate the combined equation (7) where the pass-through coefficient does not explicitly appear.

There are two additional estimation issues to be addressed. First, two of the structural variables, the computer share and the high-tech share, are only available at the two-digit level. That these variables do not vary across four-digit industries within a two-digit industry raises the possibility that the errors in (7) or (7') will be correlated within two-digit groups [Moulton, 1986]. We control for this by allowing the errors in (7) and (7') to be correlated across four-digit

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[18] Excluding the structural variables from the regression, the estimated pass-through coefficient is –1.00.

[19] To verify this, we regressed value-added prices on effective TFP, using the structural variables as instruments. In a test of over-identifying restrictions on the instruments [Newey, 1985], we reject the null hypothesis that the instruments are uncorrelated with the error term at any reasonable level of significance.

industries within each two-digit industry, where we continue to assume that the errors are uncorrelated across two-digit groups.

Second, the dependent variable in (8) and (8'), which is the contribution of each structural variable to changes in share-weighted factor price changes, is constructed using regression coefficients from the estimation of either (7) or (7'). For a given structural variable, the same estimated coefficients are embodied in the dependent variable of each industry, which implies that, by construction, the disturbance terms in (8) and (8') will be correlated across observations. We adjust the standard errors of the estimated factor-price changes in (8) and (8') to reflect this covariance structure in the errors. Details of the correction procedure are available on request from the authors.[20]

VA. Linear Decomposition

Initially, we make use of the assumed linear relation between value-added prices plus effective TFP and the structural variables, as in (7). These estimation results from this first-stage regression are shown in Table IV, where each column refers to an alternative measure of the high-technology and computer capital shares. From the discussion in section III, we expect the structural variables to positively affect productivity and to have a positive effect on the dependent variable overall. This is confirmed for all variables that are significantly estimated. Narrow outsourcing is significant in most specifications, while broad outsourcing is less so. Computers are also significant, but not other high-technology capital. It can also be noted that

[20] A further issue is that if industries are imperfectly competitive, then the measure of total factor productivity is biased because the capital share includes pure profits [Hall, 1988]. In unreported results, we controlled for this by including the log change in the output-capital ratio as a regressor in (7) and (7') [Domowitz, Hubbard, and Peterson, 1988]. Since this and other control variables (lagged total factor productivity, sectoral dummy variables) have little impact on the coefficient estimates, we report regression results for (7) and (7') with no additional controls included.

the constant term picks up all nominal changes that are common across factor prices, so the portions explained by each structural variable can be viewed as real changes.

The second-stage of the estimation is to decompose the dependent variable from (7) into that part explained by each structural variable, and then use these components as the dependent variables in (8), where the independent variables are the average shares of primary factors in the industries over 1979-1990. These regressions are shown in Table V, and the coefficients are interpreted as predicted factor-price changes due to each structural variable. In Table V we report the results using the high-technology and computer shares computed with *ex post* rental prices, while in Table VI we will show how the results are affected by using alternative measures of high-tech capital.

Consider the coefficient estimates in regression (1) of Table V. Foreign outsourcing measured narrowly (within its two-digit industry) is estimated to have increased the (real) nonproduction wage by 0.10 percent annually over 1979-1990, with a small effect on the production labor wage. Outsourcing outside the two-digit industry in regression (2) increased the nonproduction wage by 0.06 percent annually, while raising the production wage by 0.02 percent annually. Taking the difference between the estimates for nonproduction and production labor, outsourcing in the same two-digit industry led to an increase in the relative wage of nonproduction labor of 0.11 percent annually; outsourcing outside the two-digit industry also raised the relative nonproduction wage, but insignificantly. These estimates are shown in the first row of Table VI, and can be compared to the actual increase in nonproduction relative to production wages of 0.72 percent per year over 1979-1990, from Table II. Hence, our initial estimates suggest that outsourcing can account for about 15 percent of the observed increase in the relative wage of nonproduction labor, or somewhat more if we incorporate the imprecise estimates from broad outsourcing.

In column (3) of Table V, we report the same coefficients for computers. The estimates indicate that computers led to an increase in the wage of nonproduction labor by 0.25 percent annually (standard error of 0.10), with no impact on the production wage. This coefficient is also shown on the first row of Table VI, and indicates that computers can explain about 35 percent of the observed increase in the relative wage of nonproduction labor. High-technology capital in regression (4) of Table IV has no impact at all.

To examine the robustness of these results, we checked alternative measures of high-technology capital, with results reported in the remainder of Table VI. Specification (2) uses the high-technology and computer shares constructed using *ex ante* rental prices. In this case the implied change in the relative wage of nonproduction labor due to narrow outsourcing are slightly larger, as are the effects of broad outsourcing which are again imprecisely estimated. Conversely, the impact of computers is reduced and now insignificant as compared to using the *ex post* rental prices. This is similar to what we found in Table III, where the impact of computers is nearly twice as large when using *ex post* rather than *ex ante* rental prices. Specification (3) in Table VI uses the computer investment share from the *Census,* and in that case the impact of computers on the relative wage of nonproduction labor is the largest, and can account for most of the increase in the relative nonproduction wage. The largest impact of computers in the labor demand regressions reported in Table III was also obtained using the *Census* investment measure, qualitatively similar to the results in specification (3).

VB. Decomposition with Interactions

Our results above have relied on the assumed linear relation between value-added price changes plus productivity and the structural variables, as in (7). As an alternative we make use of the specification in (7'), which also includes interactions terms between the four structural variables and average log quantities for primary factors. This regression is reported in Table VII, where we use the high-technology and computer shares constructed with the *ex post* rental prices.

We argued in section III that the coefficients on the interaction terms could be interpreted as the impact of each structural variable on demand for that factor. By this interpretation, the positive and significant coefficients obtained for the interactions of outsourcing (narrow), computers and the remaining high-tech share with nonproduction labor are sensible. These variables also have negative interactions with capital, which is harder to rationalize. In any case, our interpretation of these coefficients in not exact, because they include not only the effect of the interaction terms on productivity, but also the effects on industry value added prices.

From this regression, we decompose the dependent variable into those components due to each structural variable, and use these components as dependent variables in the second-stage regressions. The independent variables are the average cost-shares for primary factors. The results for the second-stage regressions are shown in Table VIII, where specification (1) uses the *ex post* rental prices in constructing the high-tech and computer shares, as in Table VII. We see that outsourcing measured within its own two-digit industry now has a larger effect on the relative wage of nonproduction labor, increasing it by 0.51 percent annually. This is offset however, by outsourcing measured outside of its two-digit industry, which has the reverse effect. By summing these two coefficients, we find that overall outsourcing increases the relative wage of nonproduction labor by 0.29 percent annually, or about 40 percent of its actual increase.

Turning to computers in specification (1), these expenditures lead to an increase in the relative nonproduction wage of 0.56, which is equivalent to 75 percent of the increase. In the other specifications reported in Table VIII, the use of computer expenditures measured with *ex ante* rental prices in (2) leads to a smaller role of computers and a much larger role for outsourcing. Conversely, the use of the *Census* computer investment share in (3) enables computers to explain all the observed increase in the relative nonproduction wage, whereas outsourcing has a smaller effect, with broad outsourcing more than offsetting the impact of the narrow measure. Again, these differences from our benchmark specification in (1) are qualitatively similar to what we found from the labor demand regression in Table III.

VI. Conclusions

Our goal in this paper has been to estimate the relative influence of trade versus technology on wages, under a "large country" assumption. To achieve this, we have re-interpreted the conventional price regression as an identity, and then introduced structural variables that have an effect on industry productivity and prices. The structural variables were first introduced in a simple linear specification, and then including interaction terms with factor quantities. The re-interpretation of the price regression is the methodological contribution of the paper.

Our empirical results support the idea that both foreign outsourcing and expenditures on computers have played a role in the increase of the relative wage for non-production workers, with the latter variable having an impact that is twice as large as the former in the specifications using *ex post* rental prices to measure the computer share. By way of contrast, using *ex ante* rental prices to measure the computer share leads to a smaller impact of computers on the nonproduction wage, and a larger role for outsourcing. Using the *Census* investment share for computers leads to the largest impact for computers and a minimal role for outsourcing. The sensitivity of the results to the exact measure of the computer share is an empirical contribution of the paper, which carries over to other techniques, such as estimating the effects of trade and technology on labor demand.

The methodology we develop allows a set of structural variables to contribute to both sector-biased and factor-biased changes in technology. While we do find evidence that the structural variables contribute to non-neutral technological change, we cannot rule out that the possibility that the structural variables contribute to sector-biased changes as well. Thus, we are unable to decompose the contribution of these variables to sector-biased versus factor-biased technology shifts. An important task for future research is to carefully identify the nature of the changes in technology which have contributed to factor price changes.

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Table I: Dependent Variable - Log Change in Industry Price, 1979-1990

	(1)	(2)	(3)	(4)	(5)
Effective TFP	-1.000	-1.000			
	(0.007)	(0.0006)			
TFP			-0.963	-0.753	
			(0.070)	(0.075)	
Production	4.680	4.700	3.063	2.428	3.605
cost-share	(0.016)	(0.012)	(1.222)	(1.162)	(1.885)
Nonproduction	5.482	5.443	2.295	4.086	6.202
cost-share	(0.019)	(0.031)	(1.430)	(1.722)	(4.036)
Capital	3.953	3.972	7.888	8.058	9.535
cost-share	(0.008)	(0.015)	(0.781)	(0.941)	(2.187)
Materials cost-share times		0.997	1.00*	1.00*	1.219
change in materials price		(0.002)			(0.247)
Energy cost-share times		0.996	1.00*	1.00*	-0.930
change in energy price		(0.006)			(0.915)
constant		0.0101	-0.705	-0.825	-1.929
		(0.005)	(0.301)	(0.293)	(0.915)
R^2	0.999	0.999	0.896	0.806	0.429
N	447	447	447	446	446

Note: Standard errors are in parentheses. All regressions omit three industries with missing data on materials purchases or prices (SIC 2067, 2794, 3483) and are weighted by the industry share of total manufacturing shipments, averaged over the first and last period.

In column (1), the dependent variable is the log change in the industry value-added price and factor cost shares sum to one across primary factors. Effective TFP equals primal TFP minus the change in wage differentials. In columns (2)-(5), the dependent variable is the log change in the gross industry price, and the factor cost shares sum to one across all factors. The materials cost share is multiplied by the log change in the materials price; the energy cost share is treated similarly. Column (2) includes effective TFP as a regressor; column (3) replaces effective TFP with primal TFP; column (4) drops the computer industry (SIC 3573) from the sample; and column (5) also drops TFP as a regressor.

* These coefficients are constrained at unity.

Table II: Summary Statistics

	1972-1979		1979-1990	
	Average (percent)	Annual change	Average (percent)	Annual change
Change in log factor prices:				
Production labor		7.666		4.714
Nonproduction labor		7.207		5.437
Capital		8.187		3.954
Materials		9.664		3.485
Energy		15.732		3.250
Factor cost-shares:				
Production labor	12.55	-0.303	10.31	-0.156
Nonproduction labor	6.68	-0.139	6.54	0.002
Capital	24.92	-0.001	27.16	0.262
Materials	50.72	0.170	49.08	-0.261
Energy	2.02	0.113	2.23	-0.023
Other variables:				
TFP (primal)		0.279		0.467
TFP (dual)		0.275		0.467
Outsourcing (broad)	6.31	0.303	9.67	0.363
Outsourcing (narrow)	2.67	0.127	4.40	0.203
Difference	3.64	0.177	5.27	0.160
Using capital services (ex post rental prices):				
High-tech share	7.75	0.125	10.20	0.326
Computer share	4.68	-0.143	5.34	0.198
Difference	3.07	0.267	4.86	0.128
Using capital services (ex ante rental prices):				
High-tech share	5.45	0.115	7.23	0.218
Computer share	3.03	-0.047	3.21	0.053
Difference	2.42	0.162	4.02	0.164
Using computer investment:				
Computer share	1.86	--	3.75	--

Averages are computed over the first and last year of each period (except for the computer investment share which is from 1977 for the 1972-1979 period and the average over 1982 and 1987 for the 1979-1990 period), while changes are measured as an average annual change (the change in log factor prices is the annual average change x 100). Both averages and changes are weighted by the industry share of total manufacturing shipments, except for primary factors, which are weighted by the industry share of total manufacturing payments to that factor. All variables are computed over 447 four-digit SIC industries (excluding SIC 2067, 2794, and 3483), except the High-tech Share and Computer Share, which are computed over two-digit SIC industries. Those two variables are from the Bureau of Labor Statistics, as used in Berndt et al. [1992] and Morrison [1997].

Variable definitions:
Outsourcing (broad) = (imported intermediate inputs)/(total non-energy intermediates)x100
Outsourcing (narrow) = (imported intermediate inputs in the same two-digit industry as buyer)/ (total non-energy intermediates)x100
High-tech Share = (high-technology capital)/(total capital)x100
Computer Share = (computer equipment)/(total capital)x100
Computer Investment Share = (computer investment)/(total investment)x100

Table III: Dependent Variable - Change in Nonproduction Wage Share, 1979-1990

	(1) Mean	(2) Regression	(3) Regression	(4) Regression	(5) Contri-Bution
Δln(K/Y)	0.706	0.042	0.041	0.033	6.0-7.7%
		(0.014)	(0.014)	(0.012)	
Δln(Y)	1.541	0.018	0.016	0.007	2.7-7.1%
		(0.008)	(0.008)	(0.009)	
Outsourcing (narrow)	0.223	0.246	0.265	0.193	11.0-15.2%
		(0.169)	(0.175)	(0.166)	
Outsourcing (difference)	0.200	0.121	0.154	0.038	2.0-7.9%
		(0.046)	(0.050)	(0.054)	
Capital services (ex post rental prices):					
Computer share	0.251	0.206			13.3%
		(0.102)			
High-tech share (difference)	0.144	-0.039			--
		(0.129)			
Capital services (ex ante rental prices):					
Computer share	0.070		0.421		7.6%
			(0.171)		
High-tech Share (difference)	0.166		0.014		0.6%
			(0.072)		
Computer Investment:					
Computer share	6.561			0.019	31.5%
				(0.007)	
High-tech share (ex post rental prices)	0.395			0.052	5.3%
				(0.051)	
constant		0.207	0.214	0.161	41.5-55.0%
		(0.042)	(0.039)	(0.040)	
R^2		0.163	0.165	0.200	
N		447	447	447	

The mean of the dependent variable equals 0.389. Standard errors (in parentheses) are robust to heteroskedasticity and correlation in the errors within two-digit industries. The first column shows mean values of the dependent and independent variables for 1979-1990. All regressions and means are computed over 447 four-digit SIC industries and are weighted by the average industry share of the manufacturing wage bill. Δln(K/Y) is the average annual change in the log capital-shipments ratio and Δln(Y) is the average annual change in log real shipments. The outsourcing variables and the computer and high-technology shares are in annual changes and are defined in Table I and the text.

Table IV: Dependent Variable – Change in Value-Added Prices plus TFP, 1979-1990

	(1)	(2)	(3)
Independent variables:			
Outsourcing	0.064	0.080	0.040
(narrow)	(0.031)	(0.035)	(0.030)
Outsourcing	0.079	0.113	0.035
(difference)	(0.047)	(0.044)	(0.049)
Capital services (ex post rental prices):			
Computer share	0.167		
	(0.066)		
High-tech share	0.076		
(difference)	(0.072)		
Capital services (ex ante rental prices):			
Computer share		0.192	
		(0.108)	
High-tech Share		-0.048	
(difference)		(0.082)	
Computer Investment:			
Computer share			0.008
			(0.004)
High-tech share			0.093
(ex post rental prices)			(0.049)
constant	4.263	4.294	4.244
	(0.032)	(0.039)	(0.033)
R^2	0.153	0.109	0.213
N	447	447	447

All estimation is over four-digit SIC industries and equations are weighted by the average industry share of manufacturing shipments. Standard errors (in parentheses) are robust to heteroskedasticity and correlation in the errors within two-digit industry groups. The outsourcing variables and the computer and high-technology shares are all measured as annual changes; the computer investment share is measured as the average over 1982 and 1987. All variables are defined in Table I and the text.

Table V: Estimated Factor-Price Changes – 1979-1990

Dependent variable, Change in share-weighted factor prices explained by:	*Outsourcing (narrow)* (1)	*Outsourcing (difference)* (2)	*Computer Share* (3)	*High-tech Share (difference)* (4)
Mean of dep. variable	0.014	0.013	0.031	0.008
Independent variables:				
Prod. labor share	-0.010	0.020	-0.005	0.026
	(0.009)	(0.014)	(0.012)	(0.025)
Nonprod. labor share	0.099	0.063	0.248	0.007
	(0.049)	(0.039)	(0.100)	(0.004)
Capital share	0.002	-0.001	0.001	0.004
	(0.003)	(0.003)	(0.004)	(0.004)
R^2	0.256	0.227	0.505	0.310
N	447	447	447	447

Notes: Coefficient estimates used to construct the dependent variable are those from column (1) of Table III. Standard errors are in parentheses and are calculated as described in the text to account for cross-observation correlation in the disturbances that arises from the construction of the dependent variable. Observations are by four-digit SIC industry. All regressions are weighted by the average industry share of total manufacturing shipments.

Table VI: Estimated Rise in Wage Inequality –
Alternative Measures of High-Technology Capital

Dependent variable, Change in value-added prices plus TFP explained by:	*Outsourcing (narrow)*	*Outsourcing (difference)*	*Computer Share*	*High-tech Share (difference)*
(1) Using BLS capital services (ex post rental prices) for computer share and high-tech share:				
Difference between nonprod. and prod. share	0.108	0.042	0.252	-0.019
	(0.055)	(0.030)	(0.103)	(0.017)
(2) Using BLS capital services (ex ante rental prices) for computer share and high-tech share:				
Difference between nonprod. and prod. share	0.136	0.061	0.143	-0.003
	(0.063)	(0.036)	(0.082)	(n.a.)
(3) Using Census investment flow for computer share and BLS capital services (ex post rental prices) for high-tech share:				
Difference between nonprod. and prod. share	0.069	0.018	0.591	0.118
	(0.051)	(n.a.)	(0.326)	(0.064)

Notes: Coefficients shown are the difference between the estimated impact of each dependent variable on the wages of nonproduction labor and the wages of production labor. The row number identifies the column number in Table III from which coefficient estimates are taken to construct the dependent variable. Standard errors are in parentheses and are calculated as described in the text to account for cross-observation correlation in the disturbances that arises from the construction of the dependent variable. If this method fails to give a positive value for the estimated variance, then "n.a." is reported. Observations are by four-digit SIC industry. All regressions are weighted by the average industry share of total manufacturing shipments.

[a] The High-tech share is not measured as a difference from the computer share (i.e. it includes all high-tech capital) when using the Census measure of the computer share.

Table VII: Dependent Variable – Change in Value-Added Prices plus TFP, 1979-1990

Independent variables:		*Nonproduction labor interacted with:*	
Outsourcing (narrow)	0.666 (0.131)	Outsourcing (narrow)	0.116 (0.033)
Outsourcing (difference)	-0.248 (0.229)	Outsourcing (difference)	-0.092 (0.041)
Computer share	0.282 (0.233)	Computer share	0.080 (0.038)
High-tech share (difference)	1.168 (0.307)	High-tech share (difference)	-0.023 (0.050)
Production labor interacted with:		*Capital interacted with:*	
Outsourcing (narrow)	-0.002 (0.042)	Outsourcing (narrow)	-0.113 (0.031)
Outsourcing (difference)	0.156 (0.057)	Outsourcing (difference)	-0.014 (0.035)
Computer share	0.026 (0.047)	Computer share	-0.054 (0.041)
High-tech share (difference)	0.302 (0.094)	High-tech share (difference)	-0.291 (0.084)
Constant	4.259 (0.027)	N	447
		R^2	0.115

The computer share and the high-tech share are measured using BLS capital services (ex post rental prices). All estimation is over four-digit SIC industries and the regression is weighted by the average industry share of manufacturing shipments. Standard errors (in parentheses) are robust to heteroskedasticity and correlation in the errors within two-digit industry groups. The outsourcing variables and the computer and high-technology shares are all measured as annual average changes; factor levels are measured as average log quantities for 1979 and 1990.

Table VIII: Estimated Rise in Wage Inequality – Alternative Measures of High-Technology Capital

Dependent variable, Change in value-added prices plus TFP explained by:	*Outsourcing (narrow)*	*Outsourcing (difference)*	*Computer Share*	*High-tech Share (difference)*
(1) Using BLS capital services (ex post rental prices) for computer share and high-tech share:				
Difference between nonprod. and prod. share	0.507 (0.137)	-0.220 (0.089)	0.557 (0.161)	-0.014 (0.080)
(2) Using BLS capital services (ex ante rental prices) for Computer share and High-tech share:				
Difference between nonprod. and prod. share	0.578 (0.130)	-0.018 (0.055)	0.155 (0.083)	0.012 (0.116)
(3) Using Census investment flow for computer share and BLS capital services (ex post rental prices) for high-tech share:				
Difference between nonprod. and prod. share	0.253 (0.169)	-0.263 (0.106)	0.703 (0.288)	0.169 (0.248)

Notes: Coefficients shown are the difference between the estimated impact of each dependent variable on the wages of nonproduction labor and the wages of production labor. The dependent variables for the regression results reported in row (1) are constructed using coefficient estimates from Table VI. Dependent variables for the regression results reported in rows (2) and (3) are constructed using coefficient estimates from regressions similar to that in Table VI, in which the indicated measures of high-technology capital are used as independent variables. Standard errors are in parentheses and are calculated as described in the text to account for cross-observation correlation in the disturbances that arises from the construction of the dependent variable. Observations are by four-digit SIC industry. All regressions are weighted by the average industry share of total manufacturing shipments.

[a] The high-tech share is not measured as a difference from the computer share (i.e. it includes all high-tech capital) when using the Census measure of the computer share.

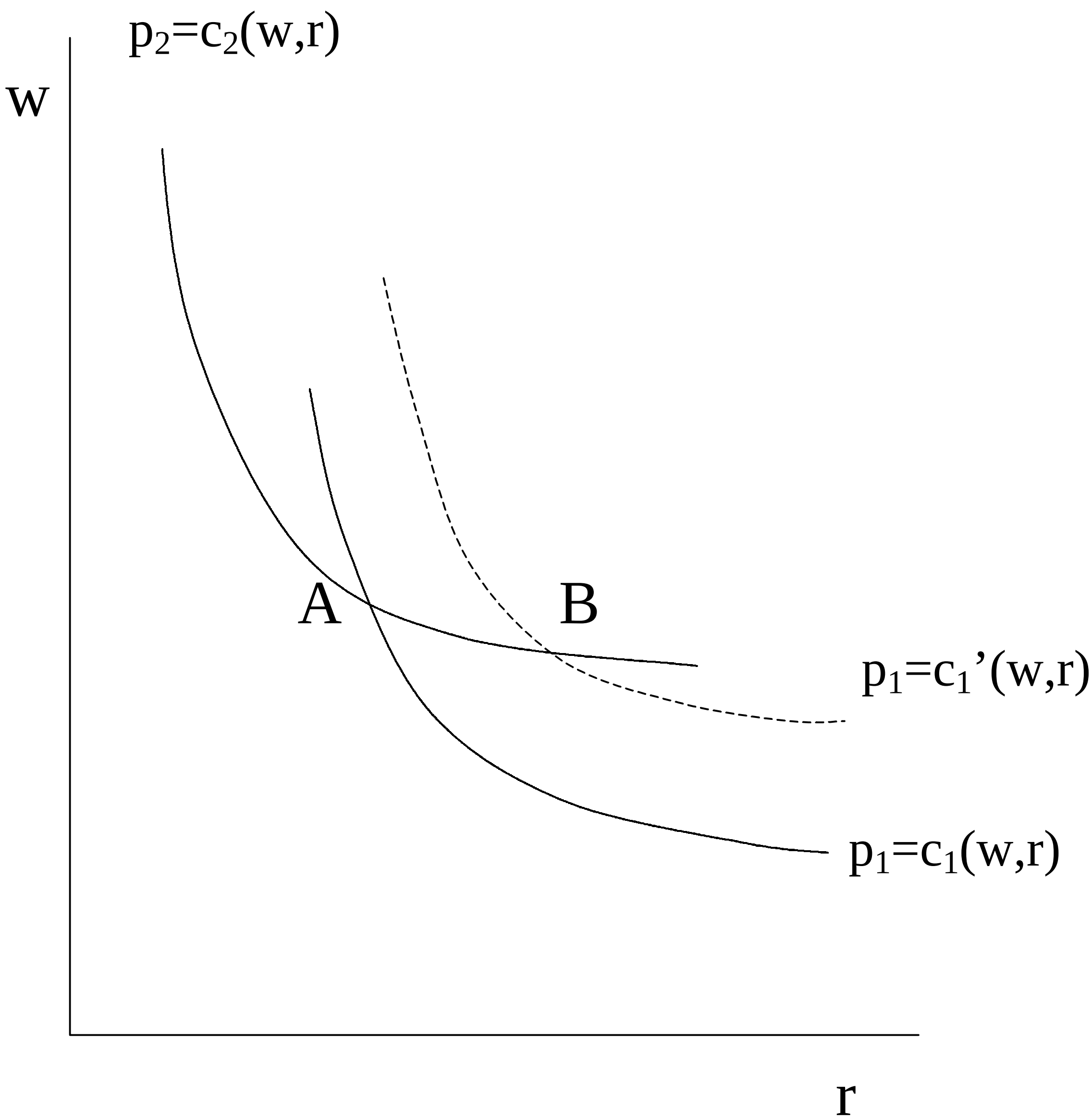

Figure 1: Hicks Neutral Technological Progress

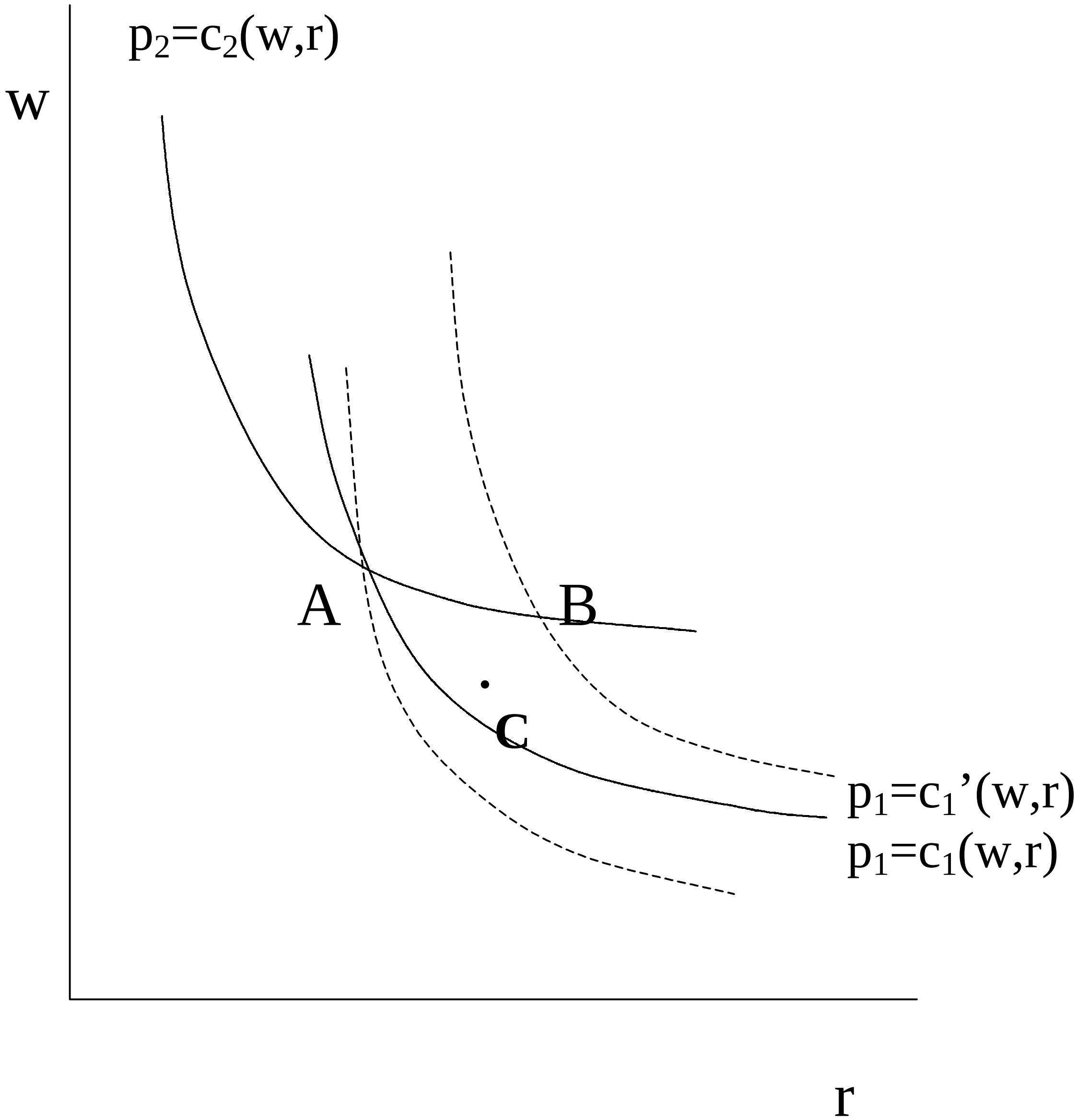

Figure 2: Skill-Biased Technological Progress