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PRODUCTIVITY MEASUREMENT AND THE IMPACT OF TRADE AND TECHNOLOGY ON WAGES: ESTIMATES FOR THE U.S., 1972-1990

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ABSTRACT

We develop an empirical framework to assess the importance of trade and technical change on the wages of production and nonproduction workers. Trade is measured by the foreign outsourcing of intermediate inputs, while technical change is measured by the shift towards high-technology capital such as computers. In our benchmark specification, we find that both foreign outsourcing and expenditures on high-technology equipment can explain a substantial amount of the increase in the wages of nonproduction (high-skilled) relative to production (low-skilled) workers that occurred during the 1980s. Surprisingly, it is expenditures on high-technology capital *other than* computers that are most important. These results are very sensitive, however, to our benchmark assumption that industry prices are independent of productivity. When we allow for the endogeneity of industry prices, then expenditures on computers becomes the most important cause of the increased wage inequality, and have a 50% greater impact than does foreign outsourcing.

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1. 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. Despite the vast literature, there is little agreement among researchers on the relative contributions of trade, technology, and other factors to the recent wages changes.[1] We believe that this is due in part to the fact that researchers have used differing methodologies, which emphasize one explanation or another. In this paper we develop an empirical framework that integrates these methodologies, and use this framework to assess the relative importance of trade and technical change. We will measure trade by the foreign outsourcing of intermediate inputs,[2] while we measure potential technical change by the shift towards high-technology capital such as computers.

Our starting point is a popular technique linking industry prices and wages: 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 technique was first used by Baldwin and Hilton (1984), and more recently by Leamer (1996), Baldwin and Cain (1997) and Krueger (1997).

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[1] Surveys with differing points of view are provided by Freeman (1995), Richardson (1995) and Wood (1995).

[2] Foreign outsourcing was first considered by Katz and Murphy (1992), and more recently by Feenstra and Hanson (1996a,b). 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,b). We will be using a measure of outsourcing constructed as in Feenstra and Hanson (1996b), which is the 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 (1996) introduces the broader term "delocalization" to indicate the many ways that pieces of the research/production/marketing processes can be moved offshore.

Using different time periods and data, these papers have obtained decidedly mixed results. Thus, neither Baldwin and Cain nor Leamer are able to reproduce the decline in relative wages of low-skilled workers (as measured by production workers) in the U.S. during the decade of the 1980s, though they have more success at estimating these changes for the 1970s; in contrast, Krueger obtains estimates for the late 1980s and early 1990s that are quite close to the actual movement in wages. The authors use somewhat different variables in the regression; Leamer includes a measure of total factor productivity to correct for technology shifts, while Krueger and Baldwin and Cain do not.

From these various results, one is left with the impression that the ability of this price regression to predict the actual change in wages is very sensitive to the precise data and specification. In this paper, we will argue that such an impression is misplaced, and that the regression of the change in industry prices on factor shares will provide a consistent estimate of the *actual* change in wages over the sample period provided that: (i) the dual measure of total factor productivity is used; and, (ii) the change in the industry-specific factor prices is uncorrelated with the industry-specific factor cost-shares. We will find that the latter condition is especially important empirically. When the change in industry-specific factor prices are correlated with the industry factor-shares, then the price regression has an omitted variable that is correlated with the factor-shares, leading to biased estimates of the change in factor prices. As shown in sections 2 and 3, we are fortunately able to measure this omitted variable with available data, so that this bias can be corrected.

Given that the price regression will provide a consistent estimate of the *actual* change in wages when these conditions are satisfied, what is its informative value? In section 4, we show that the total change in wages can be decomposed into parts attributable to the various structural changes, such as computer purchases or the foreign outsourcing of intermediate inputs. To achieve this decomposition, we rely on a regression of these structural variables on the *factor-shares* in each industry. Regressions of this type have been used by Katz and Murphy (1992), Berman, Bound and Griliches (1994), Feenstra and Hanson (1996a,b), Morrison and Siegel (1996), Autor, Katz and Krueger (1997), and Doms, Dunne, and Troske (1997), and are interpreted as the *factor-biased* demand shift induced by each structural variable. We show how these *factor-biased* shifts can be transformed into *sectoral* shifts that affect total factor productivity. That is, we decompose total factor productivity into components attributable to these structural variables. By using just one of these components in the price regression, and correcting for the omitted variable mentioned above, we can estimate the change in wages that is consistent with this structural shock alone. Repeating this over each shock, we are able to decompose the total change in wages into portions (possibly overlapping) that are due to computer purchases and foreign outsourcing.

Our empirical results are reported in sections 5 and 6. In our benchmark specification, we find that both foreign outsourcing and expenditures on high-technology equipment can explain a substantial amount of the increase in the wages of nonproduction (high-skilled) relative to production (low-skilled) workers that occurred during the 1980s. Foreign outsourcing has a greater impact on the relative nonproduction wage than does high-technology capital, though it also has a higher standard error. Surprisingly, it is expenditures on high-technology capital *other than* computers that are most important. These results are very sensitive, however, to our benchmark assumption that industry prices are independent of productivity. Krugman (1995) argues forcefully that this assumption should not be used, and Leamer (1996) has experimented with "pass-through" effects between productivity and prices. When we allow for the endogeneity of industry prices, then our results are substantially altered: expenditures on computers becomes the most important cause of the increased wage inequality, and have a 50% greater impact than does foreign outsourcing. Our conclusions are discussed further in section 7.

2. Measurement of Productivity

The typical method to derive the relation between changes in industry prices and wages is to totally differentiate the zero-profit conditions for each industry. This yields a system of equations with the (infinitesimal) change in prices on the left, the change in industry wages weighted by each factor-share on the right, and some measure of productivity also appearing on the right. While these results are certainly correct as stated, they do not provide an entirely accurate guide for empirical work. In the first place, there is no error term involved in these equations. Secondly, it is unclear how these results derived for infinitesimal changes would translate into finite first-differences of the data. Leamer (1996, p. 5, note 3; p. 23, note 5) recognizes that second-order effects might be important, but again, it is unclear how these theoretical second-order effects are captured with data measured at discrete points in time.

Our preferred method is to derive the price regression using discrete rather than infinitesimal changes. In this way, properties of the price regression that hold theoretically will also hold for any data set applied to it. The use of discrete rather than infinitesimal changes ensures that second-order effects are fully accounted for, and has been an important feature of the literature dealing with total factor productivity. We begin by outlining certain results from this literature.

To develop our notation, let Y_t denote the output of an industry that uses primary inputs

x_{it}, i=1, ..., M, and intermediate inputs y_{jt}, j=1, ..., N.[3] Denoting the vectors of inputs as x_t and y_t, we let $z_t = (x_t, y_t)$ denote the (M+N)-dimensional column vector of all inputs. The translog production function is given by:

$$\ell n f_t(z_t) = A_{0t} + (\alpha + A_t)' \ell n z_t + \frac{1}{2} \ell n z_t' \gamma \ell n z_t, \tag{1}$$

where: A_{0t} is a scalar representing neutral technological change; $\alpha > 0$ is a (M+N)-dimensional column vector and γ is a (M+N) × (M+N) symmetric matrix of fixed parameters; and A_t is a (M+N)-dimensional vector of time-varying parameters representing non-neutral technological change, as discussed below. In order for the production function (1) to be homogeneous of degree one, we assume that the elements of α sum to unity; the elements of A_t sum to zero; and the rows and columns of γ sum to zero.

The constraint that the elements of A_t sum to zero has important implications. To see this, suppose that there are just two factors, with quantities x_{1t} and x_{2t} and technological parameters $A_{1t} = -A_{2t}$. An increase in either of these parameters will *rotate* the isoquant around the point where $x_{1t} = x_{2t}$. Thus, it is impossible for this change to fully represent the effect of non-neutral technological progress, which should be a non-uniform inward shift of the isoquant. Rather, non-neutral technological progress would be represented by a combination of a change in $A_{1t} = -A_{2t}$, and an increase in the neutral technological parameter A_{0t}. When we later introduce structural variables such as computer expenditures and foreign outsourcing, we will therefore

[3] At this point we do not distinguish between imported and domestically produced inputs. This distinction is also not made in the data on intermediate demand collected by the U.S. Census, so in our empirical applications, we supplement this data with our own estimates of imported intermediate inputs.

need to allow these variables to influence *both* the non-neutral parameters A_{it}, i=1,...,N, as well as the neutral technology parameter A_{0t}.

We will let $q_t = (w_t, p_t) > 0$ denote the (M+N)-dimensional column vector of factor prices corresponding to $z_t=(x_t,y_t)$, and will suppose that these inputs are chosen to minimize total costs $q_t' z_t$ subject to $Y_t \geq f_t(z_t)$. Let s_t denote the (M+N)-dimensional vector of cost-shares $s_{it} \equiv q_{it}z_{it}/q_t' z_t$. Then from Shepard's Lemma, these can be obtained by differentiating (1),

$$s_t = \frac{\partial \ell n f_t}{\partial \ell n z_t} = \alpha + A_t + \gamma \ell n z_t \ . \tag{2}$$

Caves, Christen and Diewert (1982a, b) (hereafter CCD) show how changes in the vector of technology parameters (A_{0t}, A_t) can be represented by a scalar measure of productivity. We will present a simplified version of their analysis. From (1), changes in the output Y_t can be written as,

$$\begin{aligned} \Delta \ell n Y_t &= [\Delta A_{0t} + \Delta A_t'(\ell n z_{t-1} + \ell n z_t)/2] \\ &\quad + [\alpha + (A_{t-1} + A_t)/2]' \Delta \ell n z_t + \Delta(\tfrac{1}{2} \ell n z_t' \gamma \ell n z_t), \end{aligned} \tag{3}$$

where Δ is the first-difference operator. The first bracketed terms on the right of (3) are an overall measure of technological change, where the difference ΔA_t is evaluated using the *average* level of inputs in the two periods. We will adopt this measure as our definition of total factor productivity,

$$TFP_t \equiv \Delta A_{0t} + \Delta A_t^{'} \, (\ell nz_{t-1} + \ell nz_t)/2. \tag{4}$$

Definition (4) provides us with a scalar measure of technological change, but one that cannot be immediately implemented because the technology parameters A_{0t} and A_t are not observed. However, it turns out that (4) can be measured in a familiar manner. Using the factor shares in (2), it is straightforward to show that,

$$[\alpha + (A_{t-1} + A_t)/2]' \, \Delta\ell nz_t + \Delta(\tfrac{1}{2}\ell nz_t^{'}\gamma\ell nz_t) \;=\; \tfrac{1}{2}(s_{t-1} + s_t)' \, \Delta\ell nz_t, \tag{5}$$

where the right-side of (5) is a Tornqvist index constructed using observed shares. Combining (3), (4) and (5), we therefore find that total factor productivity can be measured as,[4]

$$TFP_t = \Delta \ell nY_t - \tfrac{1}{2} \, (s_{t-1} + \; s_t)' \, \Delta\ell nz_t \; . \tag{6}$$

While we have motivated (6) using the definition (4), CCD provide a more rigorous justification for using (6) as a measure of productivity. In particular, holding the technology parameters A_{t-1} and A_t fixed, they compare the amounts by which inputs in each period would need to be scaled up or down to produce the output of the other period. This gives two alternative measures of technological change, and it turns out that a geometric mean of these measures equals (the exponent of) the Tornqvist index in (6). From their results, we can accept our definition in (4) and the Tornqvist index in (6) as a well-justified measure of technological change.

[4] This definition of total factor productivity, and the results that CCD obtain, require that the elements of the matrix γ are constant.

It will be important for our purposes to also consider the *dual* measure of total factor productivity arising from consideration of a translog cost function:

$$\widetilde{TFP}_t = -[\Delta \ell np_t - \tfrac{1}{2}(s_{t-1} + s_t)' \Delta \ell nq_t] , \tag{7}$$

where s_{t-1} and s_t are again the observed cost-shares and we assume the observed input quantities are at their cost-minimizing values. To interpret (7), an increase in factor prices that is on average less than the increase in unit-costs indicates that technological progress has occurred. The arguments of CCD can be used equally well to justify (7) as a scalar measure of overall productivity as (6): there is no basis to prefer the primal over the dual measure of total factor productivity, though they are not equal in general.

In order to compare the primal and dual measures of productivity in (6) and (7), we need not suppose that the functional form for either production or costs is necessarily translog, but simply assume that the production function is homogeneous of degree one, so that total costs are $q_t'z_t = c_tY_t$. Then expressing the factor shares as $s_{it} = q_{it}z_{it}/c_tY_t$, it is immediate from (6) and (7) that,

$$\widetilde{TFP}_t - TFP_t = \tfrac{1}{2}(s_{t-1} + s_t)' \Delta \ell ns_t + (\ell np_t - \ell nc_t) . \tag{8}$$

This expression equals zero in the case where price equals marginal cost (as we assume below), and the production and unit-cost functions are Cobb-Douglas with only neutral technological change, so that the cost-shares are constant. In this case the production and unit-cost functions are dual, so it is not surprising that the primal and dual measures of productivity are identical. Outside of this case, TFP_t and $\widetilde{TFP}_t$ need not be equal, though we will find that their difference is very small in the sample that we consider.[5] The dual measure will be particularly useful in our theoretical discussion below.

3. The Price Regression

We will consider the measurement of total factor productivity over a number of industries i=1, ..., N, so that we add the subscript i to each variable. The vectors of input prices p_t will not vary across purchasing industries, but the wage vector w_{it} can vary, so that $q_{it} = (w_{it}, p_t)$. Treating $\Delta \ell n w_{it}$ as a random variable over industries i, we will denote its mean value by ω_t. Let us further write v_{it} as the M-dimensional column vector of cost-shares for primary inputs in industry i, and r_{it} as the N-dimensional column vector of cost-shares for intermediate inputs, so that $s_{it} = (v_{it}, r_{it})$. Then using this notation in (7), we readily obtain,

$$\begin{aligned} &\Delta \ell n p_{it} - \tfrac{1}{2}(r_{it-1} + r_{it})' \Delta \ell n p_t \\ &= -\widetilde{TFP}_{it} + \tfrac{1}{2}(v_{it-1} + v_{it})' \Delta \ell n w_{it} \qquad (9) \\ &= -\widetilde{TFP}_{it} + \tfrac{1}{2}(v_{it-1} + v_{it})' \omega_t + \tfrac{1}{2}(v_{it-1} + v_{it})\ (\Delta \ell n w_{it} - \omega_t). \end{aligned}$$

The left-hand side of (9) is the change in industry prices adjusted for the changing prices of inputs, which we shall interpret as a value-added price:

$$\Delta \ell n p_{it}^{VA} \equiv \Delta \ell n p_{it} - \tfrac{1}{2}(r_{it-1} + r_{it})' \Delta \ell n p_t \ . \qquad (10)$$

[5] The influence of price-cost margins on measures of productivity has been analyzed by Hall (1988), and more recently, Roeger (1995) argues that price-cost margins accounts for most of the difference between the dual and primal measures of TFP for U.S. manufacturing.

From the right-hand side of (9) we can define the error term,

$$e_{it} \equiv \tfrac{1}{2}(v_{it-1} + v_{it})' (\Delta \ell n w_{it} - \omega_t) \ . \tag{11}$$

Then using (10) and (11), we can rewrite (9) as,

$$\Delta \ell n p_{it}^{VA} \ = -\, T\tilde{F}P_{it} + \tfrac{1}{2}(v_{it-1} + v_{it})' \omega_t + \ e_{it} \ . \tag{12}$$

Thus, we have shown that by using the dual measure of total factor productivity in (7) we obtain the regression in (12), where the error term reflects the difference between industry-specific factor-price changes and their average value. What is exceptional about this regression is that we know the exact form of the error term – it can be measured with observable data – so that by including this term as a variable in (12), the regression will fit exactly. To illustrate this, in Table 1 we report results from estimating (12) 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. The regressions in the top half of Table 1 are for the sample of 447 industries; in the lower half of the table we also exclude the computer industry (SIC 3573), which is an extreme outlier in terms of total factor productivity.

The value-added price defined in (10) is constructed as a log-difference over the period 1972-1979 or 1979-1990, divided by the number of years in each period to obtain an annualized difference. We use the primal measure of total factor productivity, as defined in (6), expressed as an annualized difference. If we were to replace the primal with the dual measure of total factor productivity, as defined in (7), we would exactly replicate the observed annual average changes in factor prices. By using the primal measure, we more closely approximate the price regression that appears in the literature and also highlight the importance of controlling for industry-specific factor price changes. Given that the correlation between primal and dual total factor productivity is 0.999 in either time period, it does not matter much in practice which measure is used. The other independent variables are the average cost-shares (over the first and last years in each period) for production labor, non-production labor and capital. The mean values for these and other variables over the two time periods, weighted by the industry share in total manufacturing shipments, are shown in Table 2; for brevity we report the mean values with the computer industry excluded (the means are very similar when the industry is included). The mean annual changes in the prices of production labor, non-production labor and capital, as shown at the top of Table 2, are used to measure ω_t when constructing the error term defined in (11).

For each time-period in Table 1, the first regression shown includes only primal TFP and average factor-shares. The estimated coefficients can be compared to the annual changes in the prices of production labor, non-production labor and capital shown at the top of Table 2. For the 1972-1979 period, it is apparent that the coefficients of the price regressions in column (1) (with the error term not yet included as a variable) differ drastically from the actual changes in the factor prices, and this is true whether the computer industry is included in the sample or not. For the 1979-1990 period, the coefficients obtained in column (3) are quite sensitive to whether the computer industry is included or not, though in both cases, the estimated coefficients are not that close to the actual change in factor prices. The error term in (11) is included as a variable in columns (2) and (4), where it is labeled as the difference between the industry-specific and economy-wide factor price changes. Now the estimated coefficients are extremely close to the actual factor price changes reported in Table 2, and the regression fits nearly perfectly.

Empirically, what is crucial in obtaining the perfect fit of the price regression is not the difference between primal and dual total factor productivity, which is small, but the differences between industry-specific and economy-wide changes in the factor prices as reflected in the error term. When this error term is *excluded*, the resulting coefficient estimates reflect the correlation between this variable and the average factor-shares. These coefficients do not appear to provide us with any useful information. But the regression is also of limited interest when the error term is *included* as a variable, since then the coefficients just reproduce the factor-price changes observed in the data. In order to utilize the price regression for predictive purposes, we need show how the variables within this regression are related to the underlying structural changes, such as foreign outsourcing and expenditures on high-technology capital.

4. Decomposing Total Factor Productivity

We would certainly expect that purchases of high-technology capital will have some impact on total factor 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 (1996). In that model, we considered a good produced in various 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 will lower relative wages for unskilled labor: the transfer of these activities abroad is identified as foreign outsourcing. The activities remaining at home can be aggregated into a production function. With a change in underlying parameters (such as factor endowments), the range of activities done abroad can change, and this will shift the entire production function for activities done at home, and therefore show up as a change in total factor productivity.

To capture these ideas in this paper, we will consider a decomposition of total factor productivity into separate components due to high-technology equipment and foreign outsourcing. By using each one of these components in place of total TFP_t in (12), we will be able to estimate the change in factor prices consistent with that component alone. Repeating this exercise over each component, we can therefore decompose the total change in wages into (possibly overlapping) portions due to each cause.

To formalize this, we use on the definition of total factor productivity in (4), which depends on the neutral rate of technological progress (ΔA_{0t}) as well changes in the non-neutral parameters (ΔA_t) weighted by the factor quantities. For each industry, the A_t parameters can be estimated from the cost share equations in (2), re-written to include the industry subscript i:

$$s_{it} = \alpha_i + A_{it} + \gamma \ln z_{it} . \tag{2'}$$

We will estimate (2') by pooling across industries, and for simplicity, keeping the parameters γ constant across industries. We model the technology parameters A_{it} as linear functions of structural variables such as computer equipment and foreign outsourcing. Denoting the column vector of such technology variables for industry i as τ_{it}, with dimension K, we assume that:

$$A_{it} = B\tau_{it} + u_{it} , \tag{13}$$

where B is a (M+N) $\times$ K matrix of coefficients to be estimated, and u_{it} is an error term.

Substituting (13) into (2'), we obtain,

$$s_{it} = \alpha_i + B\tau_{it} + \gamma \ln z_{it} + u_{it} \ . \tag{14}$$

As discussed in section 3, we need to allow for the possibility that high-technology purchases and foreign outsourcing contribute to neutral as well as non-neutral technical progress. For each industry, we model the neutral technology parameter, A_{0it}, as a linear function of the vector τ_{it},

$$A_{0it} = \beta' \tau_{it} + v_{it}, \tag{15}$$

where β is a $(K \times 1)$ column vector of coefficients to be estimated and v_{it} is an error term. Substituting (13) and (15) into (4), we obtain the following regression equation:

$$TFP_{it} = \beta' \Delta\tau_{it} + \tfrac{1}{2}\Delta\tau_{it}' B' (\ell n z_{it-1} + \ell n z_{it}) + \varepsilon_{it}, \tag{16}$$

where $\varepsilon_{it} = \Delta u_{it}'(\ell n z_{it-1} + \ell n z_{it}) / 2 + \Delta v_{it}$. The regressors in (16) are the changes in the structural variables entered individually, and also interacted with the average log factor quantities. We can estimate β and B by jointly estimating (16) with equation (14), where we rewrite (14) in terms of first differences as,

$$\Delta s_{it} = B\Delta\tau_{it} + \gamma\Delta\ell n z_{it} + \Delta u_{it} \ . \tag{14'}$$

Using the estimated coefficients from (14') and (16), we can decompose total factor productivity into components that are attributable to the different structural variables. We define the variable ΔTFP_{ikt} as the amount by which total factor productivity in industry i would be changed if structural variable k were added into the calculation of TFP_{it} :

$$\Delta TFP_{ikt} \equiv \beta_k \Delta\tau_{ikt} + \tfrac{1}{2}\Delta\tau_{ikt} \sum_{j=1}^{M+N} b_{jk}(\ell nz_{jt-1} + \ell nz_{jt}), \tag{17}$$

where τ_{ikt} is element k of vector τ_{it}, β_k is element k of vector β, and b_{jk} is element jk of the matrix B.

Let us write the estimate of ω_t from (12) in matrix notation as,

$$\hat{\omega}_t = (V'V)^{-1}V'(\Delta \ln P_t + TFP_t - E_t), \tag{18}$$

where: V is the matrix of average factor shares in periods t-1 and t, $\Delta \ln P_t$ is the vector of elements $\Delta \ell np_{it}^{VA}$, TFP_t is the vector of TFP_{it} , and E_t is the vector of errors e_{it}. In order to estimate the effect of structural variable k on factor prices, we consider taking the difference of (12) due to the introduction of this variable, obtaining,

$$\Delta\hat{\omega}_{kt} = (V'V)^{-1}V'(\Delta TFP_{kt}). \tag{18'}$$

The interpretation of (18') is that the impact of structural variable k on factor prices is obtained by regressing ΔTFP_{kt} on the factor-shares. The regression coefficients $\Delta\hat{\omega}_{kt}$ thus show the change in factor prices that are attributable to structural variable k. It is apparent from this derivation that we are holding the change in prices $\Delta \ln P_t$ and the error term E_t *constant* when allowing the total factor productivity term to change by ΔTFP_{kt}. Our analysis is thus valid only for a small country that experiences idiosyncratic technology shocks, which take the form of ΔTFP_{ikt}, and in which the difference between the economy-wide and industry-specific wage change is held constant at E_t. These are obviously strong assumptions, and after using them in our benchmark estimation we shall go on to relax them, as described in section 6C.

To summarize the estimation strategy, we: (i) jointly estimate total factor productivity in equation (16) with the system of factor-cost share equations in (14') across industries over time; (ii) use equation (17) and the coefficient estimates from (i) to calculate the changes in total factor productivity ΔTFP_{kt} that result from adding each of the K structural variables separately; and, (iii) use equation (18') to estimate the change in primary factor prices that is attributable to each of the K structural variables.

5. Data and Preliminary Regressions

We shall apply the estimation technique described in equations (14') and (16)-(18') to U.S. manufacturing industries for the period 1972-1990. For each industry, we estimate a system of factor-share equations for five factors: production (low-skilled) labor, nonproduction (high-skilled) labor, capital, materials, and energy.[6] The data we use from Bartelsman and Gray (1996) have already been introduced in Table 2, where we report the mean value for the change in the prices and the shares for the five factors.[7] Movements in labor earnings and cost shares illustrate the rise in wage inequality that occurred during the 1980s. During the period 1979-1990, the wages of nonproduction workers increased by 5.33 percent per year, while the wages of production workers increased by only 4.74 percent, so that the wages of nonproduction relative

[6] The only data that are available on materials prices are those for domestic materials. This is why we have treated foreign outsourcing as an exogenous variable, rather than attempt to endogenize its behavior using relative prices.

to production workers rose by an average of 0.59 percent per year. 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 to 10.4 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 2. Also shown are the changes in the exogenous regressors that form the τ_{it} vector. The structural changes that we identify are the extent of foreign outsourcing, measured as 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.[8] 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:

$$\sum_j [\text{input purchases of good j by industry i}] * \left[\frac{\text{imports of good j}}{\text{consumption of good j}}\right], \tag{19}$$

[7] The price of capital is constructed by taking the value of shipments less payments to labor and materials, and dividing this by the real quantity of capital. This price therefore represents an ex-post return to capital.

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

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% in 1972 to 7.3% in 1979 and 11.6% 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 normally think of, say, the purchase of imported 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 formally made by the same company, or at least purchased in the United States. This idea is captured by restricting the four-digit industry subscript i and j in (19) 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% in 1972 to 3.1% in 1979 and 5.6% in 1990.

Also reported in Table 2 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 (1996).[9] These data distinguish capital by asset type for two-digit SIC manufacturing industries. Berndt *et al* 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***. This broad measure increased from 1.4% in 1972 to 2.8% in 1979 and 7.5% 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 was extremely small at 0.2% of the capital stock in 1972 and 0.5% in 1979, and then increased to 2.9% in 1990. We will also make use of the *difference* between the high-tech share and the computer share, which represents the fraction of the capital stock devoted to various high-technology assets *other than* office, computing and accounting machinery.

An alternative 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 (1996).[10] 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 estimating our full system, we report in Table 3 regressions of the share of the wage bill going to nonproduction workers on the structural variables and some controls. This regression is very similar to that used by Katz and Murphy (1992), Berman, Bound and Griliches

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[9] 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 this data.

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

(1994), Autor, Katz and Krueger (1996), and Feenstra and Hanson (1996a,b), 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 capital/shipments ratio as control variables. The outsourcing variables and the computer and high-technology shares are all measured as annual changes.

In columns (1) and (3) of Table 3, we report the mean values of the dependent and independent variables for each of the two periods 1972-1979 and 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 2. Following this, we report the regression coefficients in columns (2) and (4). In 1979-1990, for example, we see that the narrow definition of outsourcing had a positive and highly significant impact on the nonproduction share of the wage bill, as did computer expenditures. But the remaining outsourcing occurring outside of the same two-digit industry, and the remaining expenditures on high-technology capital, were not significant.

By multiplying the regression coefficients by the mean values for 1979-1990, we obtain the contributions shown in column (5). Of the total annual change in the nonproduction wage share of 0.390 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) account for 19% of the shift towards nonproduction labor, while computers plus other expenditures on high-technology capital account for about 30%. These estimates for outsourcing are in line with other estimates using slightly different data,[11] while the estimates for computers are consistent with Berman, Bound and Griliches (1994) and Autor, Katz, and Krueger (1997).

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

We next consider how these results are affected when the factor-share regressions are imbedded within our overall system estimation.

6. Estimation Results

The system to be estimated consists of five cost-share equations in (14') (for production labor, nonproduction labor, capital, materials, and energy), and the total factor productivity equation in (16). Given the linear dependence of the cost-share system (since the shares sum to unity), we drop the materials share equation from the estimation.[12] A cross-equation restriction implied by the theory is that the coefficients of the structural variables in the cost-share equations, B in (14'), should also enter the total factor productivity equation in (16). In all regressions we impose this cross-equation restriction, which we fail to reject when it is formally tested.

The estimation is performed by pooling over the 450 U.S. manufacturing industries at the four-digit SIC level for two time periods, 1972-1979 and 1979-1990, excluding the three industries (SIC 2067, 2794, 3483) for which materials data are unavailable. Thus, all variables are constructed as differences or averages within these two periods. We choose these time periods as they correspond to business cycle peaks in the U.S. economy. We experimented to some degree with allowing for fixed-effects at the two-digit level, but these did not greatly affect the results. However, the computer industry (SIC 3573) was an extreme outlier and had to be excluded to obtain any sensible results. This industry had an extremely high rate of total factor productivity during the 1979-1990 period. When this industry is pooled with the others in the

[12] The coefficients from this equation are still reported in Table 4, and are constructed using the condition that the coefficients of each structural (or factor quantity) variable sum to zero across the five equations.

total factor productivity equation (16), it results in unrealistically large estimates for predicted wage changes (even when a two-digit fixed effect is included for SIC 35).

The estimation results are shown in Table 4, where we report only the coefficients of the structural variables, and for brevity, omit reporting the coefficients of the factor-quantities that occur within the factor-share equations.[13] Of particular interest is the comparison of each structural variable across the various cost-share equations. Thus, during the period 1979-1990, the narrow measure of outsourcing shifts demand away from production labor (with a coefficient of -0.134 and significant) and has only a small effect on nonproduction labor (with a coefficient of -0.026). A similar pattern holds for the remaining portion of outsourcing (the difference between the broad and narrow measures), though to a smaller extent. Expenditures on computers also shifts demand away from production and towards non-production labor (with coefficients of -0.182 and 0.068, respectively), and has even a stronger impact than outsourcing. Surprisingly, remaining expenditures on high-technology capital have an insignificant effect on both production and non-production labor, and instead show up as strongly correlated with the capital share (with a coefficient of 0.314).

The coefficients of the structural variables in the cost-share equation also appear in the total factor productivity equation (16), and there multiply the structural variables *interacted with* each average factor-quantity.[14] This somewhat unfamiliar construction of variables follows from

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[13] From (14'), the log quantity of each factor should enter each share equation. However, these factor-quantities would clearly be endogenous, especially for labor, materials and energy. So instead, we estimated a reduced-form of the share equations, which included the log quantity of shipments and of capital, along with the various structural variables. This formulation has the same independent variables that were used in the wage-share equation shown in Table 3. Both shipments and capital generally entered the cost-share equations with very small coefficients.

[14] Thus, in the TFP equation (16), there will be the four structural variables entered linearly, and for each of these, as many as five interaction terms between the structural variable and each average factor-quantity. However, on cross-sectional data these average factor-quantities are meaningful only if their units are the same across industries. This is clearly not the case for materials or energy, since their price indexes depend on the units in which the outputs of various industries are measured, which are arbitrary. In other words, we have no way to meaningfully compare the

the specification of the non-neutral technological parameters A_{it} in the translog production function; see equations (1)-(6). In section 2 we argued that it is also important to allow the neutral technological parameters A_{0it} to also be influenced by the structural variables. In that case the structural variables will enter the total factor productivity equation linearly. These coefficients are shown in the last row of Table 4 for each time period.

We see that outsourcing (either measure) is negatively related to total factor productivity in the period 1972-1979, but has the expected positive sign over 1979-1990, though these coefficients are not significant. The computer share is also positively correlated with total factor productivity, and is significant in the second period. A puzzling pattern holds for the remaining expenditures on high-technology capital, which are *positively* related to productivity in 1972-1979 but *negatively* related in 1979-1990 (both these effects are significant). These results can be compared to Berndt and Morrison (1995), who *also* find a negative impact of high-technology capital on total factor productivity, but do not separate computers from the aggregate of high-tech capital. The lack of a positive impact of computers on productivity has been a puzzle since this result was first found in the late 1980s (see the discussion in Baily and Gordon, 1988), and is still being examined is recent research such as Oliner and Sichel (1994) and Hornstein and Krusell (1996). Thus, the negative impact of high-tech capital and positive impact of computers for 1979-1990, as reported in Table 4, is part of the general puzzling pattern of these variables on productivity as found by other authors.

Most recently, Siegel (1997) has argued that the negative impact of computers is due in

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real magnitude of materials or energy across industries. Accordingly, we omitted these interaction terms from (16), and for each structural variable, included just the interaction terms with production and nonproduction labor (both in man-hours) and capital (in constant 1987 dollars).

part to measurement error, and obtains a positive relationship between computer expenditures and productivity using disaggregate data.[15] While we will not attempt to incorporate the corrections for measurement error that he employs, his results provide motivation for using several different measures of the computer and high-technology variables. These will be used in our analysis in section 6B, after first presenting our benchmark specification in the next section.

6A. Exogenous Industry Prices

We now turn to the central question of our research: to what extent the various structural variables account for the change in relative wages over the 1980s. To isolate the impact of each structural variable on wages, we first use (17) to calculate ΔTFP_{ikt} for each industry i and structural variable k, for the two time periods t. This magnitude indicates the amount that each structural variable contributes to total factor productivity. Then, following (18'), we regress ΔTFP_{ikt} on average factor shares for the primary factors (production labor, nonproduction labor, and capital). As described in section 4, this method of estimating the impact on factor prices assumes that changes in productivity *do not* affect product prices, and also do not affect the industry-specific component of factor prices. We refer to this benchmark specification as using "exogenous industry prices." Note also that since ΔTFP_{kt} is an estimated variable rather than data, the standard errors from this regression cannot be obtained from the usual OLS formula, and our construction of the appropriate standard errors is discussed in the Appendix. These regressions are reported in Table 5, where the column numbers indicate which set of coefficient estimates from Table 4 are used to calculate ΔTFP_{ikt}.

[15] Siegel and Griliches (1991, Table 12) find a positive (partial) cross-sectional correlation between the *Census* computer share and total factor productivity in a subset of U.S. manufacturing industries.

The coefficients in Table 5 indicate the amount by which primary factor prices are impacted by the structural variable in question. Consider the period 1979-1990. The coefficient estimates on the production labor cost-share indicate that outsourcing led to a *decline* in the production wage of 0.25% annually under the narrow measure, and 0.44% under the remaining outsourcing. Conversely, foreign outsourcing *increased* the nonproduction wage by 0.39% annually for the narrow measure, and 0.14% for the remainder. Taking the difference between these estimates, outsourcing in the same two-digit industry led to an increase in the relative wage of nonproduction labor of 0.64%, and outsourcing outside of the industry by an additional 0.58% annually. These point estimates are shown in the first row of Table 6, along with their standard errors, which are rather large. The actual increase in nonproduction wages relative to production wages for the period 1979-1990 was 0.59 percent per year, from Table 1. Hence, we conclude that either measure of foreign outsourcing can fully account of the rise in nonproduction wages relative to production wages for the period 1979-1990, though these impacts are rather imprecisely estimated.

In columns (3) and (4) of Table 5, we report the same coefficients for computers and high-technology capital. Again, consider the period 1979-1990. The estimates in column (3) indicate that computers led to a decline in the wage of nonproduction labor by 0.57% annually, but a further and unrealistically large decline of 2.62% annually in the wage of nonproduction labor. We attribute the unrealistic impact on nonproduction labor to that fact that computers led to a estimated *decline* in total factor productivity within our sample, which can be seen from the *negative* mean value for ΔTFP_{ikt}, reported in column (3) of Table 5 for 1979-1990. Thus, despite that fact that computers are positively related to productivity when entered linearly, the *total* impact on productivity must also take into account the interaction terms between changes in computers expenditures and the average quantity of each primary factor employed in the industry: this is the formulation in (17).[16] Each of these interaction terms is multiplied by its coefficient for that factor and that structural variable in Table 4. Thus, when the change in the computer share is interacted with the average quantity of capital in 1979-1990, it has a coefficient of -0.301 (from Table 4) in constructing ΔTFP_{ikt}: industries that use more capital therefore have a larger *negative* impact of computers on productivity.

The negative impact of computers on total factor productivity has the effect of *reducing* the relative wage of nonproduction workers in our estimates. This should be interpreted as a Stolper-Samuelson effect: the negative impact on productivity is analogous to a price *fall* in the industries using computers intensively, and since the use of this factor is correlated with the use of nonproduction workers, it leads to a fall in their relative wages. In theory, this is entirely consistent with the impact that computers have on increasing the demand for nonproduction workers within each industry, since the Stolper-Samuelson effect works across rather than within industries. As a statement about reality, however, we find the negative impact of computers on the relative wage of nonproduction workers hard to believe. There are at least two features of our benchmark estimation that may have contributed to this result. The first is the particular measure of the computer and high-technology capital stock we have used, and in our sensitivity analysis of the next section, we will experiment with alternative measures. The second is that we have held product prices and the industry-specific wage differentials fixed in the estimation, whereas we might expect these variable to be affected by the structural variables and associated productivity changes. This feature will be addressed in section 6C.

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[16] Recall from the last note, that we are including just the interaction terms with production and nonproduction labor (both in man-hours) and capital (in constant 1987 dollars).

Turning to high-technology capital in column (4), our estimates show that production wages fell by 0.62% annually due to these expenditures, while nonproduction wages fell by the smaller amount of 0.26% annually. Taking the difference between these, the relative wage of nonproduction labor would have risen by -0.26+0.62=0.36% annually. This magnitude is shown in the first row of Table 6, and is significant at the 95% level. Again, this can be compared to the actual growth of the relative nonproduction from 0.59 percent per year, from Table 1. Thus, high-technology capital can account for about 60 percent of the rise in nonproduction wages relative to production wages for the period 1979-1990. The point estimates indicate that foreign outsourcing has a greater on the relative nonproduction wage than high-technology capital, though the impact of outsourcing is much less precisely estimated. In order to put these results in perspective, we need to investigate how sensitive they are to alternative specifications.

6B. Sensitivity Analysis

As a first alternative, we change the measurements of the computer and high-tech shares. Recall that these variables are constructed by the BLS, which estimates the real stock of many different assets within each two-digit industry for the U.S. The computer share that we have used is measured as the real stock of office, computing and accounting machinery assets within each industry, divided by the total stock of capital assets in that industry; the high-tech share also includes the stocks of communications equipment, science and engineering instruments, and photocopy and related equipment. Instead of using these *stock* measures, we can construct a rental price for each capital asset, and multiply the stocks by their respective rental prices to obtain a *flow* of capital services for each asset, in each two-digit industry.[17] Then the computer

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[17] The rental prices we use are the same as those used by Berndt and Morrison (1995) and Morrison (1996), and are the *ex ante* rental prices excluding any capital gains term. The formula for these rental prices is given by eq. (29) in

and high-tech shares are measured as the flow of capital services from these assets, relative to the flow of services from all capital assets in each two-digit industry.

We have re-estimated the system using these alternative measures of the computer and high-tech shares. In the second set of results in Table 6, we report the final estimates for the estimated effect of each structural variable on the nonproduction wage minus the production wage. In comparison with our benchmark specification in the first row, we see that the narrow measure of foreign outsourcing declines in importance, but the remaining outsourcing (outside of the two-digit purchasing industry) has a large impact of 1.28% annually on the nonproduction relative to the production wage, and this coefficient is significant. The computer share retains its unusual *negative* impact on the relative nonproduction wage, but the remaining high-tech capital has a negligible impact in this specification.

As a third specification, we consider using the measure of the computer share obtained from the *Census*, which asked firms to report what fraction of investment was devoted to computer purchases in 1977, 1982 and 1987. The numerator and denominator of this variable are both *investment* flows, which therefore differ from the flows of *capital services* that were used in the second specification, and which we continue to use for measuring the high-tech share. The final results for this specification are shown in the third set of results in Table 6.[18] These are qualitatively similar to our benchmark case in the first row, except that all the coefficients are now larger, and especially so for the computer share. Note that the foreign outsourcing (outside of the two-digit purchasing industry) is again significant, though the high-tech share is not.

Harper, Berndt, and Wood (1989), where the Moody rate for Aaa-rates bonds is to measure the *ex ante* interest rate, and the capital gains term is excluded.

[18] The *Census* computer share is available for 1977, 1982 and 1987. For the 1979-1990 regression reported in Table 6, we use the average of the shares in 1982 and 1987.

We noted above that the unusual effect of the computer share on the relative wage of nonproduction labor seemed to reflect the negative total impact of this variable on productivity (as illustrated by the negative value of ΔTFP_{ikt} for the computer share in 1979-1990, in Table 5). This impact was in turn related to the negative coefficient of -0.301 appearing in Table 4, which is the effect of computers on the capital share. This coefficient *also* multiplies the interaction term between changes in the computer share and the average level of capital, in the total factor productivity equation (16). To see whether this interaction term is driving our results, we have re-estimated the system while *omitting* the interaction terms between the industry capital stock and each of the structural variables from equation (16), and also from the construction of the components ΔTFP_{ikt} in (17).[19]

While we do not report these results in detail, we have found that they are very similar to those already reported within Table 6. In particular, the computer share still has an unusual *negative* impact on the relative nonproduction wage. This result occurs because when the capital interactions terms are omitted, then the computer share enters linearly into the total factor productivity equation with a *negative* coefficient of -0.912 for 1979-1990, and the total impact of computer on productivity (as measured by the mean value of ΔTFP_{ikt}) is also negative. This sign pattern occurs for all three specifications already reported in Table 6, and in each case, the computer share continues to have the unusual, negative impact on the relative wage of nonproduction labor.[20]

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[19] Recall from note 14 that we exclude energy and materials from the interaction terms, because their real magnitudes cannot be meaningfully compared across industries. With the industry capital stocks also excluded, then the only interaction terms that enter the total factor productivity equation are between production and nonproduction labor and each of the structural variables.

[20] We also experimented with omitting seven two-digit sectors that import primary inputs, but these imports do not reflect our conception of outsourcing: these industries were tobacco, lumber, paper, printing, chemicals, petroleum refining, and stone, clay and glass. Omitting these leads to a large increase in the impact of outsourcing (narrow), an

6C. Endogenous Industry Prices

Our benchmark specification has assumed that the product prices and the industry-specific wage differentials are not affected by productivity changes. The restrictiveness of this assumption can be understood as follows. The system we examine contains 450 final goods industries and just three primary factors of production (capital, production labor, nonproduction labor). Beginning from a state in which all goods are produced, a change in technology that alters factor prices would almost surely induce complete specialization over some range of goods. To avoid this movement towards specialization, we would have to suppose that either: (a) the technology shock is to some extent common across countries, so that it also affects industry prices (as argued by Krugman, 1995); or (b) there is some component of human and physical capital that is specific to individual industries, so that factor prices can differ across industries (as occurs in our data).

To incorporate both these alternative assumptions, we extend the estimation procedure as described in section 4. In particular, suppose that change in prices ($\Delta \ln P_t$) and in the industry-specific wage differentials (E_t) depend on the change in the structural variables ($\Delta\tau_t$) and on total factor productivity according to:

$$\Delta \ln P_t - E_t = \delta' \Delta\tau_t + \lambda \, TFP_t \,, \tag{20}$$

where δ is a (Kx1) column vector of coefficients, and λ is the scalar "pass-through" coefficient between productivity and the industry prices/wage-differentials. Leamer (1996) has

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increase in the impacts of outsourcing (broad) and high-technology (other than computers), and no change in the (negative) impact of computers.

experimented using various values of the pass-through coefficient ranging from zero to -1. Rather than pick some values, we will estimate the coefficients of (20), treating total factor productivity as endogenous. As instruments, we can use the interaction terms between the structural variables ($\Delta\tau_t$) and the average factor-quantities that are correlated with total factor productivity according to (16). This allows us to estimate (20) for each time period. For 1972-1979 we obtain an estimate (standard error) for the pass-through coefficient of -1.725 (0.076), and for 1979-1990 we obtain -1.040 (0.086).

The initial system estimates are the same as those reported in Table 4, and from (17), we use these to compute the change in total factor productivity (ΔTFP_{kt}) due to impact of each structural variable. From (20), we can also compute the change in the industry price/wage-differential due to each structural variable k, $\Delta \ell n P_{kt} - \Delta E_{kt} \equiv \delta_k \Delta\tau_{kt} + \lambda\, \Delta TFP_{kt}$. Then we use these imputed effects of each structural variable to estimate the change in factor-prices as:

$$\hat{\omega}_{kt} = (V'V)^{-1} V' (\Delta \ell n P_{kt} + \Delta TFP_{kt} - \Delta E_{kt}), \qquad (18'')$$

which extends our earlier estimation in (18'). Thus, the change in factor-prices due to each structural variable is estimated by a regression of the level of industry factor-shares V on the dependent variable $\Delta \ell n P_{kt} + \Delta TFP_{kt} - \Delta E_{kt}$, which measures the impact of that structural variables on prices, productivity and the industry-specific wage-differentials.

The results from these regressions are reported in Table 7. Consider the period 1979-1990. The coefficients on narrow outsourcing (i.e. within the same two-digit sector), indicate that production wage fell by 0.24% and nonproduction wages rose by 0.58% annually due to this variable. Thus, the relative wage of nonproduction workers was increased by 0.82% annually, which is reported in the first row of Table 8. The broad outsourcing variable (i.e. outside the same two-digit sector) has the surprising effect of decreasing the relative nonproduction wage, but this is imprecisely measured. Turning to the computer share in column (3), we estimate that these expenditures had the effect of increasing the production wage by 0.37% annually, but increasing the nonproduction wage even more by 1.62%. The difference between these indicate an increase in the relative nonproduction wage of 1.25% annually, which is also reported in the first row of Table 8. Finally, expenditures on high-technology capital other than computers has a negligible estimated impact on either production or nonproduction wages.[21]

To summarize, by allowing for the endogeneity of industry product prices and wage-differentials, we obtain results that are quite different from our benchmark specification: the computer variable now has a 50% greater impact on the relative nonproduction wage than does foreign outsourcing (measured narrowly), while remaining expenditures on high-technology capital have no impact at all. Indeed, the computer and foreign outsourcing variables each explain more than the full increase in the relative nonproduction wage, which was 0.59% per year (from Table 1), reflecting that fact that our procedure does not ensure that the individual impacts will add up to the observed total. Focusing on the relative impact of the structural variables, it is noteworthy that the 50% greater impact for computers than (narrow) outsourcing is the same as what we found in Table 3, where we measured the impact of the structural variables on the wage-share of nonproduction labor. Thus, the full system estimation, allowing for the endogenous response of industry prices, arrives at similar results for 1979-1990 to the simple estimation of labor demand effects.

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[21] The standard errors reported in Table 7 and 8 take into account the fact that the dependent variable is itself constructed from estimated parameters, as described in the Appendix. In some cases the constructed standard errors fail to be positive, as occurs for the coefficients on the high-tech share.

We have checked the robustness of the results with endogenous industry price by re-estimating the system using different measures of high-technology capital and computers. These alternative measures are the same as those used in the sensitivity analysis of Table 6, and the results reported in Table 8 follow the same format. In the second set of results in Table 8, we replace the high-technology and computer stocks with corresponding measures of the service flows from these variables (both of these are from BLS data). The corresponding estimate of the pass-through coefficient λ is -1.069 (0.073). This specifications increases the absolute magnitude of all the coefficients as compared to the first set of results, but leaves their relative magnitudes about the same. In particular, the computers shares still have about a 50% greater impact on increasing the relative nonproduction wage than does (narrow) outsourcing.

In the third set of results in Table 8, we replace the BLS computer variable with the *Census* measure of the share of investment devoted to computers. The estimate of the pass-through coefficient λ is -1.027 (0.074). This specification results in almost a doubling of the estimated impact of computers as compared with our first set of results (and also a doubling of its standard error). The impact of computers on the relative nonproduction wage is now so large – 2.36% as compared to the actual increase of 0.59% annually – that we place greater emphasis on the results obtained with the BLS measures of computers and high-technology capital.

7. Conclusions

One goal of this paper has been to develop the links between three empirical methodologies: (i) the regression of changes in prices on productivity and factor cost-shares; (ii) the regression of changes in cost-shares for nonproduction and production labor on industry characteristics and structural variables; (iii) the regression of total factor productivity on various structural variables. Having established these links in a discrete-time framework, we have estimated the implied system of equations over cross-sectional data for U.S. manufacturing. The second goal is to see what can be learned for the determinants of the increasing wage gap between nonproduction and production workers that occurred during the 1980s.

On the first goal, we feel that we have made substantial progress. We have argued that technique (i) has an omitted variable as it is often specified, namely, the difference between industry-specific and economy-wide changes in factor prices. But when this variable is included in the price regression, along with (dual) total factor productivity, then the regression essentially becomes an identity. To move beyond this stalemate, we have suggested taking differences of the equation with respect to structural variables that affect both total factor productivity and factor-prices. This is achieved by exploiting methods (ii) and (iii), which we argue can be estimated as a system with cross-equation constraints: the amount by which each structural variable influences a factor cost-share *also* determines the amount by which this structural variables (interacted with the quantity of that factor) influences total factor productivity. We are not aware of these cross-equation restrictions having previously been utilized. We expect that this system of equations is well-suited to other applications, such as the time-series analysis of particular industries.

We have estimated the resulting system over a number of specifications. In our benchmark case, which assumes that product prices and industry-specific wage-differentials are exogenous, we find that outsourcing both within and outside of the two-digit purchasing industry lead to an increase in the relative nonproduction wage that is roughly equal to its actual increase over 1979-1990 (0.59% annually), though these impacts are not significantly estimated. Expenditures on high-technology capital leads to an increase in the relative wage of nonproduction labor that explains about 60% of its actual change over 1979-1990, and is significant, but the use of computers leads to an unusual *reduction* in the relative wages of nonproduction workers. These qualitative results are preserved when several different measures of high-technology capital and computers are used.

We then considered an alternative specification where industry prices were treated as endogenous. In this case, expenditures on computers have the greatest impact on increasing the relative nonproduction wage, followed by outsourcing within the same two-digit industry. The effect of foreign outsourcing outside of the two-digit industry is measured quite imprecisely, while expenditures on high-technology capital other than computers has a negligible impact on wages. The results are obtained with an estimated "pass-through" coefficient between total factor productivity and industry prices of about -1. This compares with a pass-through coefficient implicitly used in our benchmark specification of zero. In these two cases, we have found that the relative importance of foreign outsourcing versus high-technology or computer expenditures is reversed. If we were to consider alternative values for the pass-through coefficient between zero and -1, we expect that the impact of our structural variables would lie in-between our current results. This means that we cannot precisely assess the relative importance of foreign outsourcing versus high-technology capital without know the extent to which *either* of these structural changes is spread abroad. In other words, the impact of these variables within a country cannot be separated from their global effects. Quantifying the global impacts of these structural changes is an important topic for future research.

Appendix

The standard errors reported in Tables 5 and 6 take into account the fact that we do not observe the "true value" of ΔTFP_{kt}, and instead construct this variable as in equation (17), which we write in vector notation as:

$$\Delta T\hat{F}P_{kt} = Z_k \hat{\beta}_k \, ; \tag{A1}$$

where: Z_k includes all the right-hand side variables in (17), i.e. the structural variable k and its interaction with the average factor quantities; and $\hat{\beta}_k$ is the vector of estimated coefficients on these variables (our notation in this Appendix will differ from the main text). We can write these estimates as $\hat{\beta}_k = \beta_k + S_k \eta_k$, where β_k is the true coefficient vector, η_k is vector of iid N(0,1) random variables, and $S_k S_k' = \Omega_k$ is the variance-covariance matrix for $\hat{\beta}_k$. Since the "true" value of ΔTFP_{kt} equals $Z_k\beta_k$, we can use this relation with (A2) to obtain,

$$\Delta T\hat{F}P_{kt} = \Delta TFP_{kt} + Z_k S_k \eta_k . \tag{A2}$$

We will let denote the ε_k denote disturbance term associated with the regression of the "true" value of ΔTFP_{kt} on the average factor-shares V,

$$\Delta TFP_{kt} = V \Delta\omega_k + \varepsilon_k . \tag{A3}$$

We assume that ε_k is uncorrelated with η_k. Combining (A2) and (A3), the coefficients reported in Tables 5 and 6 are obtained from the regression,

$$\Delta T\hat{F}P_{kt} = V \Delta\omega_k + \varepsilon_k + Z_k S_k \eta_k . \tag{A4}$$

Letting $\Delta\hat{\omega}_{kt}$ denote the OLS estimate of the coefficients in this regression, the variance-covariance matrix of $\Delta\hat{\omega}_{kt}$ is then,

$$\sigma_\varepsilon^2(V'V)^{-1}+(V'V)^{-1}V'Z_k\Omega_k Z_k' V(V'V)^{-1}, \tag{A5}$$

where σ_ε^2 is the variance of ε_k. In order to obtain this variance, let u_k denote the residuals from the OLS regression of $\Delta T\hat{F}P_{kt}$ on V. Then we treat $u_k u_k'$ as an estimate of the variance-covariance matrix of the errors in (A4), namely, as an estimate of $\sigma_\varepsilon^2 I + Z_k\Omega_k Z_k'$. It follows that an estimate of σ_ε^2 can be obtained by averaging the diagonal elements of $u_k u_k' - Z_k\Omega_k Z_k'$. Given this estimate, the standard errors of $\Delta\hat{\omega}_{kt}$ are computed from (A5).

This procedure needs to be extended when we also allow for the endogeneity of the industry product prices and wage-differentials, as described in section 6C. We will write the coefficients estimates of eq. (20) as: $\hat{\delta}_k = \delta_k + \sigma_{\delta k}\mu_k$, where μ_k is a N(0,1) random variable, and $\sigma_{\delta k}^2$ is the variance of $\hat{\delta}_k$; and $\hat{\lambda} = \lambda + \sigma_\lambda \nu$, where ν is also a N(0,1) random variable, and σ_λ^2 is the variance of $\hat{\lambda}$. Using these, the independent variable that we construct is,

$$\begin{aligned}\Delta\ell n\hat{P}_{kt} + \Delta T\hat{F}P_{kt} - \Delta\hat{E}_{kt} &= \hat{\delta}_k\Delta\tau_k + (1+\hat{\lambda})\Delta T\hat{F}P_{kt} \\ &= \delta_k\Delta\tau_k + (1+\lambda)\Delta T\hat{F}P_{kt} + \sigma_{\tau k}\mu_k\Delta\tau_k + \sigma_\lambda\nu\,\Delta T\hat{F}P_{kt}.\end{aligned} \tag{A6}$$

This is our estimate of the "true" variable $\Delta\ell nP_{kt} + \Delta TFP_{kt} - \Delta E_{kt} = \delta_k\Delta\tau_k + (1+\lambda)\Delta TFP_{kt}$, and we suppose that this "true" independent variable equals $V\Delta\omega_k + \varepsilon_k$. Substituting (A2) into (A6), we therefore obtain,

$$\Delta\ell n\hat{P}_{kt} + \Delta T\hat{F}P_{kt} - \Delta\hat{E}_{kt} =$$

$$V\Delta\omega_k + \varepsilon_k + (1+\lambda+\sigma_\lambda v)Z_k S_k \eta_k + \sigma_{\tau k}\mu_k \Delta\tau_k + \sigma_\lambda v Z_k \beta_k, \tag{A7}$$

where all terms after the first on the right-hand side are incorporated into the random error.

Letting $\Delta\hat{\omega}_{kt}$ denote the OLS estimate of the coefficients in this regression, the variance-covariance matrix of $\Delta\hat{\omega}_{kt}$ is then,

$$\sigma_\varepsilon^2(V'V)^{-1} + (1+2\lambda+\lambda^2+\sigma_\lambda^2)(V'V)^{-1}V'Z_k\Omega_k Z_k'V(V'V)^{-1} +$$

$$(V'V)^{-1}V'[\sigma_{\delta k}^2\Delta\tau_k\Delta\tau_k' + \sigma_\lambda^2 Z_k\beta_k\beta_k'Z_k']V(V'V)^{-1}, \tag{A8}$$

where σ_ε^2 is the variance of ε_k. In order to obtain this variance, let u_k denote the residuals from the OLS regression in (A7). Then we treat $u_k u_k'$ as an estimate of the variance-covariance matrix of the errors in (A8). It follows that an estimate of σ_ε^2 can be obtained by averaging the diagonal elements of $u_k u_k' - [(1+2\lambda+\lambda^2+\sigma_\lambda^2)Z_k\Omega_k Z_k' + \sigma_{\delta k}^2\Delta\tau_k\Delta\tau_k' + \sigma_{\lambda k}^2 Z_k\beta_k\beta_k'Z_k']$. Given this estimate, the standard errors of $\Delta\hat{\omega}_{kt}$ are computed from (A8). In constructing this estimate along with (A8), we replace $\lambda^2+\sigma_\lambda^2$ by $\hat{\lambda}^2$, since $E\hat{\lambda}^2 = \lambda^2+\sigma_\lambda^2$, and we replace $\beta_k\beta_k'$ by $\hat{\beta}_k\hat{\beta}_k' - \Omega_k$, since $E\hat{\beta}_k\hat{\beta}_k' = \beta_k\beta_k' + \Omega_k$.

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Table 1: Dependent Variable - Log Change in Industry Value-Added Price

Including the Computer Industry

Time Period	1972-1979		1979-1990	
	(1a)	(2a)	(3a)	(4a)
TFP	-0.996	-1.001	-0.963	-1.001
(primal)	(0.020)	(0.0006)	(0.018)	(0.0006)
Production	2.889	7.603	3.063	4.690
cost-share	(0.922)	(0.029)	(0.744)	(0.024)
Nonproduction	10.529	7.246	2.265	5.446
cost-share	(1.395)	(0.043)	(0.952)	(0.031)
Capital	4.884	8.156	7.888	3.994
cost-share	(0.626)	(0.020)	(0.402)	(0.014)
Industry minus average		0.999		0.996
factor-price change		(0.0015)		(0.0015)
constant	1.120	0.017	-0.705	-0.009
	(0.173)	(0.006)	(0.124)	(0.004)
R^2	0.860	0.999	0.896	0.999
N	447	447	447	447

Excluding the Computer Industry

Time Period	1972-1979		1979-1990	
	(1b)	(2b)	(3b)	(4b)
TFP	-0.999	-1.002	-0.753	-1.002
(primal)	(0.027)	(0.0008)	(0.027)	(0.001)
Production	2.908	7.607	2.428	4.697
cost-share	(0.930)	(0.029)	(0.683)	(0.024)
Nonproduction	10.513	7.243	4.086	5.437
cost-share	(1.400)	(0.043)	(0.889)	(0.031)
Capital	4.887	8.157	8.058	3.988
cost-share	(0.628)	(0.020)	(0.367)	(0.015)
Industry minus average		0.999		0.997
factor-price change		(0.002)		(0.002)
constant	1.120	0.016	-0.825	-0.007
	(0.174)	(0.006)	(0.114)	(0.004)
R^2	0.774	0.999	0.806	0.999
N	446	446	446	446

Note: Standard errors are in parentheses. Both sets of regressions omit three industries with missing data on materials purchases (SIC 2067, 2794, 3483); the lower set also excludes the computer industry (SIC 3573). All regressions are weighted by the industry share of total manufacturing shipments.

Table 2: Summary Statistics

	1972-1979		1979-1990	
	Average (Percent)	Annual Change	Average (Percent)	Annual Change
Change in log factor prices:				
Production Labor		7.888		4.744
Non-prod. Labor		7.469		5.334
Capital		8.540		3.646
Materials		9.767		3.558
Energy		15.749		3.230
Factor cost-shares:				
Production Labor	12.60	-0.304	10.40	-0.154
Nonprod. Labor	6.58	-0.137	6.44	0.008
Capital	24.87	-0.004	27.06	0.263
Materials	53.92	0.331	53.85	-0.092
Energy	2.03	0.114	2.26	-0.024
Other variables:				
TFP (primal)		0.075		0.232
TFP (dual)		0.072		0.233
Outsourcing (broad)	6.27	0.301	9.42	0.337
Outsourcing (narrow)	2.65	0.128	4.35	0.201
Difference	3.62	0.173	5.07	0.136
High-tech Share	2.08	0.193	5.13	0.403
Computer Share	0.36	0.038	1.71	0.218
Difference	1.72	0.155	3.42	0.185

Notes: Averages are computed over the first and last year of each 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. All variables are computed over 446 four-digit SIC industries (excluding SIC 2067, 2794, 3483 and computers 3573), 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 (1996).

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 stock)/(total capital stock)]x100

Computer Share = [(computer equipment stock)/(total capital stock)]x100

Table 3: Dependent Variable - Change in Nonproduction Wage Share

Time Period	1972-1979		1979-1990		
	(1) Mean Value	(2) Regression	(3) Mean Value	(4) Regression	(5) Contri- bution
Dependent Variable	0.108		0.390		
Δln(K/Y)	0.664	0.022 (0.009)	0.959	0.038 (0.010)	9.3%
Δln(Y)	2.709	0.010 (0.009)	1.154	0.016 (0.007)	4.7%
Outsourcing (narrow)	0.155	-0.017 (0.050)	0.221	0.263 (0.051)	14.9%
Outsourcing (difference)	0.243	0.063 (0.040)	0.175	0.091 (0.067)	4.1%
Computer Share	0.047	0.190 (0.472)	0.269	0.341 (0.096)	23.5%
High-tech Share (difference)	0.116	-0.091 (0.097)	0.180	0.136 (0.105)	6.3%
constant		0.054 (0.041)		0.144 (0.039)	36.9%
N		446		446	
R^2		0.029		0.174	

Notes:
Standard errors are in parentheses. The second and fourth columns show the mean values of the dependent and independent variables. All regressions and means are computed over 446 four-digit SIC industry (excluding SIC 2067, 2794, 3483 and 3573), and are weighted by the average industry share of the manufacturing wage bill. Δln(K/Y) is the change in the log capital/shipments ratio and Δln(Y) is the change in log real shipments. The outsourcing variables and the computer and high-technology shares are all measured as annual changes, and are defined in Table 2 and the text.

Table 4: System Estimation Results

Time period:	1972-1979				
	(1)	(2)	(3)	(4)	
Independent Variables:	*Outsourcing (Narrow)*	*Outsourcing (Difference)*	*Computer Share*	*High-tech Share (Difference)*	R^2
Dependent variables:					
Prod. Labor Share	-0.022	-0.051	-0.400	0.024	0.327
	(0.026)	(0.022)	(0.266)	(0.043)	
Nonprod. Share	-0.035	-0.040	-0.205	-0.079	0.331
	(0.017)	(0.015)	(0.182)	(0.030)	
Capital Share	0.125	0.085	-0.346	-0.707	0.093
	(0.057)	(0.049)	(0.571)	(0.093)	
Energy Share	-0.036	-0.002	0.064	0.244	0.180
	(0.021)	(0.018)	(0.221)	(0.036)	
Materials Share	-0.031	0.008	0.888	0.518	n.a.
	(0.058)	(0.050)	(0.574)	(0.094)	
TFP (primal)	-0.604	-0.119	6.983	5.916	0.048
	(0.434)	(0.333)	(4.357)	(0.792)	

Time period:	1979-1990				
Independent Variables:	*Outsourcing (Narrow)*	*Outsourcing (Difference)*	*Computer Share*	*High-tech Share (Difference)*	R^2
Dependent variables:					
Prod. Labor Share	-0.134	-0.081	-0.182	0.013	0.390
	(0.018)	(0.027)	(0.039)	(0.042)	
Nonprod. Share	-0.026	0.017	0.068	0.010	0.058
	(0.014)	(0.022)	(0.032)	(0.034)	
Capital Share	0.088	-0.072	-0.301	0.314	0.074
	(0.052)	(0.080)	(0.115)	(0.121)	
Energy Share	-0.003	0.066	0.003	-0.075	0.092
	(0.011)	(0.017)	(0.025)	(0.027)	
Materials Share	0.074	0.072	0.412	-0.262	n.a.
	(0.049)	(0.077)	(0.108)	(0.117)	
TFP (primal)	0.187	0.673	1.618	-2.150	0.061
	(0.403)	(0.557)	(0.879)	(0.830)	

Notes: All system estimation over 446 four-digit SIC industry (excluding SIC 2067, 2794, 3483 and computers 3573), and equations are weighted by the average industry share of the manufacturing shipments. For expositional simplicity, estimates for other regression coefficients are excluded.

Table 5: Estimated Factor Price Changes - Exogenous Industry Prices

Dependent variable, ΔTFP_{ikt} *due to:*	*Outsourcing (narrow)*	*Outsourcing (difference)*	*Computer Share*	*High-tech Share (difference)*[a]
Time period:		1972-1979		
	(1)	(2)	(3)	(4)
Mean of Dep. Variable	0.022	0.031	0.067	-0.051
Independent Variables:				
Prod. Labor Share	-0.050	0.079	0.348	0.495
	(0.034)	(0.062)	(0.342)	(0.617)
Nonprod. Labor Share	0.362	0.462	0.291	0.496
	(0.576)	(0.619)	(0.503)	(0.438)
Capital Share	-0.098	0.086	0.139	-0.186
	(0.111)	(0.034)	(0.036)	(0.482)
Constant	0.029	-0.031	-0.030	-0.100
	(0.028)	(0.027)	(0.017)	(0.056)
R^2	0.036	0.131	0.138	0.025
N	446	446	446	446
Time period:		1979-1990		
Mean of Dep. Variable	0.041	-0.031	-0.332	0.111
Independent Variables:				
Prod. Labor Share	-0.249	-0.436	-0.568	-0.617
	(0.247)	(0.375)	(0.265)	(0.255)
Nonprod. Labor Share	0.393	0.144	-2.624	-0.259
	(0.480)	(0.051)	(0.700)	(0.150)
Capital Share	-0.021	0.011	0.031	0.259
	(0.091)	(0.031)	(0.133)	(0.191)
Constant	0.048	0.002	-0.112	0.123
	(0.051)	(0.011)	(0.047)	(0.052)
R^2	0.028	0.109	0.226	0.147
N	446	446	446	446

Notes: Standard errors are in parentheses, and are constructed as described in the Appendix. Observations are by four-digit SIC industry. All regressions are weighted by the average industry share of total manufacturing shipments. Column numbers refer to the regression in Table 4 from which coefficient estimates are taken to calculate the dependent variable.

Table 6: Sensitivity Analysis - Exogenous Industry Prices

Dependent variable, ΔTFP_{ikt} *due to:*	*Outsourcing (narrow)*	*Outsourcing (difference)*	*Computer Share*	*High-tech Share (difference)*[a]
Time period:		1979-1990		
Using BLS capital stocks for Computer share and High-tech share (as in Tables 4, 5):				
Difference between Nonprod. and Prod. Share	0.642 (0.713)	0.580 (0.431)	-2.056 (0.719)	0.358 (0.195)
Using BLS capital flows (stock times rental price) for Computer share and High-tech share:				
Difference between Nonprod. and Prod. Share	0.312 (0.715)	1.278 (0.487)	-1.784 (0.854)	0.093 (0.118)
Using Census capital flow for Computer share and BLS capital flow for High-tech share:				
Difference between Nonprod. and Prod. Share	1.004 (0.751)	0.972 (0.449)	-6.942 (1.507)	0.526 (0.523)

Notes: Standard errors are in parentheses, and are constructed as described in the Appendix. Observations are by four-digit SIC industry. 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.

[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 7: Estimated Factor Price Changes - Endogenous Industry Prices

Dependent variable, $\Delta \ell n P_{kt} + \Delta TFP_{kt} - \Delta E_{kt}$:	*Outsourcing (narrow)*	*Outsourcing (difference)*	*Computer Share*	*High-tech Share (difference)*[a]
Time period:		1972-1979		
	(1)	(2)	(3)	(4)
Mean of Dep. Variable	-0.001	-0.002	-0.005	0.006
Independent Variables:				
Prod. Labor Share	0.076	-0.086	-0.494	-2.146
	(0.067)	(0.067)	(0.388)	(0.710)
Nonprod. Labor Share	-0.590	-0.532	-0.546	-1.312
	(0.606)	(0.657)	(0.549)	(0.551)
Capital Share	0.135	-0.080	-0.147	1.562
	(0.119)	(0.038)	(0.059)	(0.552)
Constant	-0.039	0.032	0.026	0.191
	(0.032)	(0.029)	(0.011)	(0.070)
R^2	0.074	0.112	0.138	0.353
N	446	446	446	446
Time period:		1979-1990		
Mean of Dep. Variable	0.001	0.001	0.008	0.0005
Independent Variables:				
Prod. Labor Share	-0.238	0.177	0.367	-0.005
	(0.107)	(0.168)	(0.152)	(0.070)
Nonprod. Labor Share	0.584	-0.026	1.621	-0.002
	(0.223)	(0.013)	(0.449)	(n.a.)
Capital Share	-0.096	0.017	0.115	0.032
	(0.047)	(0.015)	(0.070)	(0.088)
Constant	0.053	-0.006	0.019	0.003
	(0.022)	(0.005)	(0.022)	(0.018)
R^2	0.200	0.109	0.468	0.165
N	446	446	446	446

Notes: Standard errors are in parentheses, and are constructed as described in the Appendix. 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.

Table 8: Sensitivity Analysis - Endogenous Product Prices

Dependent variable, $\Delta \ell n P_{kt} + \Delta TFP_{kt} - \Delta E_{kt}$:	*Outsourcing (narrow)*	*Outsourcing (difference)*	*Computer Share*	*High-tech Share (difference)*[a]
Time period:		1979-1990		
Using BLS capital stocks for Computer share and High-tech share (as in Tables 4, 7):				
Difference between	0.822	0.203	1.254	0.003
Nonprod. and Prod. Share	(0.318)	(0.190)	(0.401)	(n.a.)
Using BLS capital flows (stock times rental price) for Computer share and High-tech share:				
Difference between	0.897	-0.522	1.485	-0.006
Nonprod. and Prod. Share	(0.324)	(0.242)	(0.424)	(n.a.)
Using Census capital flow for Computer share and BLS capital flow for High-tech share:				
Difference between	0.712	-0.358	2.363	0.384
Nonprod. and Prod. Share	(0.329)	(0.212)	(0.881)	(0.209)

Notes: Standard errors are in parentheses, and are constructed as described in the Appendix. 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. 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.

[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.