INTERNATIONAL TRADE AND LABOR-DEMAND ELASTICITIES

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ABSTRACT

In this paper I try to determine whether international trade has been increasing the own-price elasticity of demand for U.S. labor in recent decades. The empirical work yields three main results. First, from 1960 through 1990 demand for U.S. production labor became more elastic in manufacturing overall and in five of eight industries within manufacturing. Second, during this time U.S. nonproduction-labor demand did not become more elastic in manufacturing overall or in any of the eight industries within manufacturing. If anything, demand seems to be growing less elastic over time. Third, the hypothesis that trade contributed to increased elasticities has mixed support, at best. For production labor many trade variables have the predicted effect for specifications with only industry controls, but these predicted effects disappear when time controls are included as well. For nonproduction labor things are somewhat better, but time continues to be a very strong predictor of elasticity patterns. Thus the time series of labor-demand elasticities are explained largely by a residual, time itself. This result parallels the common finding in studies of rising wage inequality. Just as there appears to be a large unexplained residual for changing factor prices over time, there also appears to be a large unexplained residual for changing factor demand elasticities over time.

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1 Introduction

In recent years a number of economists have researched whether international trade has contributed to the ongoing rise in the U.S. relative price between more-skilled and less-skilled labor. There is still no clear consensus, however, about how much international trade has mattered. Many people find this ambiguity difficult to reconcile with the large amount of anecdotal evidence that trade has been placing substantial "pressure" on labor markets.

In this paper I look for pressure not in the *prices* for labor but rather in the *elasticities of demand* for labor. My goal is to determine whether international trade has been increasing firms' equilibrium own-price elasticity of demand for labor.

In theory trade can change labor-demand elasticities without changing labor prices. As will be discussed, trade can make labor demand more elastic in two main ways: by making output markets more competitive and by making domestic labor more substitutable with foreign factors. Trade can generate these effects without also generating product-price changes and, via the Stolper-Samuelson theorem, factor price changes.[1] This means that finding little effect of trade on wages can be entirely consistent with finding a large effect of trade on elasticities. If this is the case then the proper interpretation of trade "pressuring" labor markets might hinge on elasticities, not prices.[2]

To determine trade's effect on labor-demand elasticities the empirical work proceeds in two stages. First, using the NBER Productivity Data Base I estimate a time series from as far back as 1960 through 1990 of own-price demand elasticities for production labor and nonproduction labor for U.S. manufacturing overall and for manufacturing disaggregated into eight industries. The goal is to identify robust patterns over time in labor-demand elasticities. Second, I regress these estimated elasticities on several plausible measures of trade, technology, and institutional factors

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[1] For example, in a Heckscher-Ohlin trade model if an economy's autarky relative endowment equals that of the rest of the world then when that country opens to trade it experiences *no* change in product prices and thus (via the Stolper-Samuelson theorem) *no* change in wages. But this opening can make foreign factors more substitutable with domestic ones and can make product markets more competitive.

[2] Rodrik (1997, p. 26) argues there is reason to think that the main impact of globalization on labor markets falls on elasticities rather than on prices. In a Heckscher-Ohlin world pressure on factor prices comes from trade with countries with dissimilar relative endowments. But pressure on elasticities can come from trade with *any* kind of countries.

which can influence labor-demand elasticities. These stage-two regressions try to explain patterns in the stage-one elasticities with patterns in trade, technology, and labor-market institutions.

The empirical work yields three main results. First, over time demand for production labor has become more elastic in manufacturing overall and in five of eight industries within manufacturing. The elasticity fluctuated around -0.6 until the mid-1970s, but then it dropped steadily to around -1.3 by 1990. Second, nonproduction-labor demand has not become more elastic in manufacturing overall or in any of the industries within manufacturing. Almost all estimates range somewhere between -0.5 and -0.8, and if anything, demand seems to be growing less elastic over time.

Third, the hypothesis that trade contributed to increased elasticities has mixed support, at best. For production labor many trade variables have the predicted effect for specifications containing as regressors only these variables or them plus industry fixed effects. However, these predicted effects generally disappear when time controls are included as well. For nonproduction labor things are somewhat better. Four plausible trade variables--narrow and broad outsourcing, the foreign-affiliate share of U.S. multinational corporations' assets, and net exports as a share of shipments--have the predicted sign at at least the 90% level of significance even when both industry and time controls are included. For both labor types time is a very strong predictor of elasticity patterns, with production (nonproduction) demand becoming progressively more (less) elastic. This result parallels the common finding in studies of wage inequality that measures of trade and/or technology explain only a minority of wage patterns. Just as there appears to be a large unexplained residual for changing factor prices, there also appears to be a large unexplained residual for changing factor demand elasticities.

This paper has four subsequent sections. Section two presents the theory of how trade can make factor demands more elastic. Section three presents the stage-one regressions: related empirical work, the data, specification issues, and results. Section four similarly presents the stage-two regressions. Section five concludes.

2 Theoretical Framework

The Economic Importance of Labor-Demand Elasticities

It's easy to understand how changing labor prices are important. When less-skilled wages decline absolutely people can suffer welfare declines. When less-skilled wages decline relative to more-skilled wages greater political discord can arise as well.

Why are changing labor-demand elasticities important? Rodrik (1997) explains three important implications of more-elastic factor demands. First, higher elasticities shift the wage and/or employment incidence of non-wage labor costs (e.g., payroll taxes) towards labor away from employers. Second, higher elasticities trigger more-volatile responses of wages and/or employment to any exogenous shock to labor demand.[3] U.S. within-group income inequality has become more variable in recent years, and Rodrik argues that increasing elasticities might have contributed to this. Third, higher elasticities shift from labor towards capital the bargaining power over rent distribution in firms which enjoy extranormal profits. This shift in power might help explain the declining role of unions in the United States.

The Labor Economics of Labor-Demand Elasticities

This paper draws on both labor theory and international-trade theory to understand what determines labor-demand elasticities.

On the labor side, Hamermesh (1993) summarizes what determines a firm's equilibrium own-price labor-demand elasticity with "the fundamental law of factor demand" (p. 24). Modifying his notation slightly, here is the law.

$$\text{(1)} \qquad \eta_{LLj} = -[1-s]\sigma_{LL} - s\eta_j$$

In (1), η_{LLj} is firm j's own-price labor-demand elasticity defined to be negative; s is labor's share of firm total revenue; σ_{LL} is the constant-output elasticity of substitution between labor and all other factors of production; and η_j is the product-demand elasticity facing firm j in its output market. The variables s, σ_{LL}, and η_j are all defined to be positive.

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[3]The distribution of volatility between wages and employment depends on the slope of the labor-supply schedule. If labor supply is perfectly inelastic (elastic) then labor-demand shocks trigger only wage (employment) volatility.

As written in (1), η_{LLj} consists of two parts. The first, $-[1-s]\sigma_{LL}$, is the "substitution effect." It tells, for a given level of output, how much the firm substitutes away from labor towards other factors when wages rise. This term $-[1-s]\sigma_{LL}$ is often called the *constant-output* labor-demand elasticity, distinct from the *total* elasticity η_{LLj}. The second part of (1), $- s\eta_j$, is the "output effect" or "scale effect." It tells how much labor demand changes after a wage change thanks to the change in the firm's level of output. Higher (lower) wages imply higher (lower) costs and thus, moving along the firm's product-market demand schedule, lower (higher) firm output.

When wages rise, both the substitution and scale effects reduce labor demand. The firm substitutes away from labor towards other factors, and with higher costs the firm produces less output such that it demands less of all factors. Thus, $\eta_{LLj} < 0$: labor demand slopes downward.

How International Trade Affects Labor-Demand Elasticities: Scale Effect

What does international-trade theory say about equation (1)? Several models predict that both η_j and σ_{LL} in equation (1) depend on various aspects of a country's international-trade patterns.

First, consider η_j. Differentiation of (1) with respect to η_j shows that as product demand becomes more elastic (i.e., η_j rises), so does labor demand (i.e., η_{LLj} falls): $\frac{\partial \eta_{LLj}}{\partial \eta_j} = -s < 0$. The larger is labor's share in the firm's costs and revenue, the stronger is the pass-through from η_j to η_{LLj}. This effect of trade on labor demand is an application of one of the four Hicks-Marshallian laws of factor demand: "The demand for anything is likely to be more elastic, the more elastic is the demand for any further thing which it contributes to produce" (Hicks, 1964, p. 242).

Many models predict that trade makes a country's product markets more competitive. This can happen through at least two channels. One is domestic trade-policy liberalization that forces domestic firms to face heightened foreign competition. The other is developments abroad--such as factor accumulation and trade liberalization--that are communicated to domestic producers as more-intense foreign competition.

Different trade models predict different magnitudes for η_j. Models with perfectly-competitive product markets (e.g., Hecksher-Ohlin models) have the extreme result of infinitely-elastic η_j's and thus infinitely-elastic η_{LLj}'s. Empirical estimates of actual η_{LLj}'s never approach infinity, however, so relying on these models alone leaves a gap between trade theory and the data. But several trade models of imperfect competition predict that trade liberalization makes factor demands more elastic--but not infinitely so.

One such model posits a single domestic firm competing against foreign producers while protected by an import quota which creates for the firm a linear residual-demand schedule. Helpman and Krugman (1989, chapter 3) show that relaxing the quota forces the domestic firm to cut output and price. It can be demonstrated that at this new output (on the new residual-demand schedule) product demand is now more elastic.[4] All else equal, this increases the firm's labor-demand elasticities.

A second example is a monopolistically-competitive industry producing for Dixit-Stiglitz consumers who value product variety. In this model the representative firm is usually assumed to face a demand elasticity equal to the elasticity of substitution (EOS) among product varieties in consumers' utility function. But the actual demand elasticity is only *approximately* equal to the EOS. It equals EOS *plus* a second term, $\frac{(1\text{-EOS})}{N}$, where N is the number of firms in the industry. Thus for a given level of N each firm faces an isoelastic demand schedule with $\eta_j = \text{EOS} + \frac{(1\text{-EOS})}{N}$. As N rises η_j rises ($\frac{\partial \eta_j}{\partial N} = \frac{-(1\text{-EOS})}{N^2} > 0$ because EOS is assumed to be greater than one) and each firm's entire demand schedule shifts in. The number of firms--both domestic and foreign--competing in this industry can rise as a result of domestic trade liberalization or foreign developments such as factor accumulation which shifts the foreign output mix towards this industry. All else equal, the increase in η_j triggered by more firms increases (in absolute value) each firm's η_{LLj}.

[4] Let the firm's demand be $Q = (a\text{-}x)\text{-}bP$, where x is the level of the quota. Assume constant marginal production costs equal to c (This assumption is not crucial: the result holds for increasing marginal costs as well.). Given this market structure, the equilibrium η_j equals $\frac{-(x\text{-}a\text{-}bc)}{(a\text{-}x\text{-}bc)} > 0$. Relaxing the quota increases x. The effect of this on η_j is given by $\frac{\partial \eta_j}{\partial x} = \frac{2bc}{(a\text{-}x\text{-}bc)^2} > 0$. Thus as the quota relaxes, the equilibrium η_j becomes more elastic.

A third example is a monopolistically-competitive industry producing for ideal-variety consumers whose upper-tier utility function between the heterogeneous product and the homogeneous product is Cobb-Douglas. Helpman and Krugman (1985) show that this market structure implies that each firm faces a η_j equal to N, the number of firms in the industry. As in the previous example, international trade can increase N--and thus η_{LLj}--in many ways.

How International Trade Affects Labor-Demand Elasticities: Substitution Effect

The second way through which international trade can increase η_{LLj} is through σ_{LL}, the constant-output elasticity of substitution between labor and all other factors. Suppose that a firm is vertically integrated with a number of production stages. With international trade the firm can move stages abroad either within the firm by becoming a multinational enterprise and establishing a foreign affiliate (e.g., (Helpman 1984)) or arm's length by buying the output of those stages from other firms (e.g., Feenstra and Hanson (1996)). Trade thus gives firms access to foreign factors of production as well as domestic ones, either directly in foreign affiliates or indirectly through intermediate inputs. Trade expands the set of factors firms can substitute towards in response to higher domestic wages beyond just domestic non-labor factors to include foreign factors as well. So a move from autarky to some trade should increase σ_{LL}, and freer trade should tend to increase σ_{LL} even further. And note that firms need not actually access foreign factors to increase σ_{LL}: just the ability to do so is sufficient.[5]

Differentiation of (1) with respect to σ_{LL} shows that as this substitutability increases labor demand becomes more elastic (i.e., η_{LLj} falls): $\frac{\partial \eta_{LLj}}{\partial \sigma_{LL}} = -[1-s] < 0$. Also, the smaller is labor's share in the firm's costs and revenue, the stronger is the pass-through from σ_{LL} to η_{LLj}. For any

[5]Notice that in subsequent empirical work the price of imported intermediate inputs is captured in the variable measuring the price of all U.S. intermediate inputs. But what is at issue here in trade changing the elasticity of substitution is accessibility to these inputs (i.e., not their prices). Also, if multinationals actually hire foreign factors of production, then for them the relevant factor prices include both domestic and foreign ones. The empirical work below on the U.S. manufacturing sector uses only domestic factor prices. One reason is that since 1977 (earlier data do not exist for this issue), the domestic parents of U.S. multinationals have accounted for only about 50% of total U.S. manufacturing employment. Another reason is the empirical work below uses changes wages, not their levels. Given differences in countries' business cycles and growth trends, it seems plausible to suppose that U.S. wage changes are close to orthogonal to foreign wage changes. If this is the case, omitting foreign wages even for multinationals only would not bias other parameter estimates. See Slaughter (1995) for an analysis U.S. multinationals' labor demand.

given σ_{LL}, higher wages trigger larger (smaller) shocks to labor demand the less (more) important labor is in total costs.

To summarize: in theory, international trade can increase the equilibrium own-price elasticity of demand for domestic factors of production by increasing either η_j or σ_{LL}.[6]

Firm-Level Labor Demand Versus Country-Level Labor Demand

It is worth emphasizing that the theory just presented is for the labor demand of an individual firm. In contrast, Leamer (Leamer and Levinsohn 1995, Leamer 1995, Leamer 1996) has recently discussed the labor demand of an entire country in the Heckscher-Ohlin framework. In particular, he has pointed out that an implication of the Factor-Price-Equalization (FPE) Theorem for a sufficiently diversified economy is that its *national* labor demand is infinitely elastic. That is, a change in the national endowment of factors does not change national relative wages. Instead, it alters the national mix of outputs as predicted by the Rybczynski Theorem.[7] Leamer (1995) argues that renaming the FPE Theorem the "Factor-Price-Insensitivity Theorem" would more accurately describe this issue.

It is important to emphasize that firm labor-demand elasticities and national labor-demand elasticities are two conceptually distinct ideas. Although both use the phrase "labor-demand elasticity," these two concepts describe two conceptually distinct optimization problems. The firm's labor-demand elasticity derives from its profit-maximizing optimal input choice given exogenous factor prices, product prices, and production technology. The national labor demand

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[6]Changes in labor's share of costs, s, also change η_{LLj}. But it is not clear how international trade affects s. For example, if trade liberalization changes a country's relative product prices and thus its relative factor prices, within each industry firms attempt to substitute towards using more of the now-cheaper factor(s) of production and less of the now-dearer factor(s) of production. It is not clear how cost shares change overall. In part it depends on the production technology. With linear technology full substitution is possible, such that a rise in one factor's price drives its s to zero and the other factor's s to one. With Leontief technology no substitution is possible, such that a rise in one factor's cost raises its s but lowers the s of the other factor. Also, even when the direction of change in s is known the effect on η_{LLj} is not unambiguous. It depends on the relative sizes of σ_{LL} and η_j. For example, for manufacturing overall the share of production-worker wages in total shipments fell from about .15 in 1960 to .10 in 1990. All else equal, this might have made production-labor demands more elastic if σ_{LL} was greater than η_j.

[7]This result assumes that the change in national outputs is sufficiently small relative to total world output that world product prices are unaffected. If the national output changes do change world relative product prices, then domestic relative factor prices will change as well through the Stolper-Samuelson process.

elasticity derives from a country's optimal output-mix choice given exogenous factor endowments, product prices, and production technology.

Hamermesh (1993, p. 1) emphasizes what firm-level elasticities are about when he writes: "What is the demand for labor? The simplest answer to this question is that the demand for labor is any decision made *by an employer* [italics original] regarding the company's workers." Equation (1) summarizes the key elements of this firm-level labor demand. Similarly, Leamer (1995, p.42) implicitly makes the distinction very clear when he emphasizes that the national-labor-demand implications of the Heckscher-Ohlin model do not depend in any way on σ_{LL}, one of the two key components in equation (1). "The Factor-Price-Insensitivity Theorem, the Stolper-Samuelson Theorem, and the Heckscher-Ohlin Theorem do not depend at all on substitution between inputs within sectors. These theorems apply even if input ratios are technologically fixed. The Factor-Price-Insensitivity Theorem and the Heckscher-Ohlin Theorem are driven fundamentally by changes in the mix of products." This intersectoral national resource allocation is an entirely different concept than how each firm within each sector allocates resources.

In general, then, there is no necessary link between labor-demand elasticities of firms and countries. National elasticities can be infinite while firm-level elasticities are finite--perhaps even zero for constant-output elasticities. This paper is analyzing whether trade has made labor demand more elastic for U.S. firms, not the country overall. Determining whether U.S. national labor demand has become more elastic over time would require an alternative empirical strategy. Haskel and Slaughter (1997) discuss these different notions of labor-demand in greater detail.

3 Stage-One Regressions: Estimating Labor-Demand Elasticities

Literature Survey

Drazen, Hamermesh, and Obst (1984), Lawrence and Lawrence (1985), and Maskus and Bohara (1985) consider how labor-demand elasticities depend on product-market conditions. Drazen, Hamermesh, and Obst (1984) find some empirical evidence that labor-demand elasticities vary with product-market demand. Lawrence and Lawrence (1985) theorize that declining industries (such as U.S. steel in the 1970s) realize less-elastic labor demands--and thus more aggressive wage demands from their workers--because the substitutability between labor and capital declines when product-market demand declines. Maskus and Bohara (1985) estimate constant-output factor-demand elasticities for one year on industries grouped as importables or exportables.

Revenga (1992), Abowd and Lemieux (1993), and Borjas and Ramey (1995) don't focus on labor-demand elasticities, but they do address how product-market competitiveness affects wages and employment. Revenga (1992) tests how import product-market competition moves wages and employment in certain U.S. industries. Abowd and Lemieux (1993) study how international-price competition affects the collective-bargaining outcomes in Canadian firms. And Borjas and Ramey (1995) study how foreign competition can reduce firms' product-market power and thus squeeze labor rents.

Finally, Levinsohn (1993) and Harrison (1994) present direct firm-level evidence on how trade liberalization affects product-market competitiveness in manufacturing. Both studies (Levinsohn of Turkey and Harrison of the Ivory Coast) find that post-liberalization, product-market demand became more elastic (as proxied by price-cost markups). Neither study links these product-market developments to labor markets, but these more-elastic product markets should have led to more-elastic labor markets as well.

In contrast to these related works, this paper is the first to estimate time patterns for U.S. labor-demand elasticities and then correlate these estimates with measures of international trade.[8]

Data Description for Demand Estimation

The ideal data for this project would be firm-level data because firms are the relevant units that actually demand factors. But no publicly-available firm-level data set exists for large sections of the U.S. economy, so the next best alternative is industry-level data. Hamermesh acknowledges this tradeoff: more-disaggregated data are closer to theory but are also harder to acquire. In reality

[8]Richardson and Khripounova (1996) also estimate the time pattern of U.S. labor demand elasticities, but their approach is patterned after regressions run in an earlier draft of this paper.

very few studies of labor-demand elasticities have used firm-level data. Indeed, Hamermesh's literature survey cites only three of estimates of η_{LLj} generated from firm-level data.[9]

This paper uses the NBER's Productivity Data Base (1997). This industry-year panel tracks both inputs and outputs for all 450 4-digit SIC U.S. manufacturing industries from 1958 through 1991. Unfortunately, there are not comparable data for the service sector (in particular, with labor disaggregated somehow). From this data set I use the following variables: number of production and nonproduction workers; payroll of production and nonproduction workers; price indexes for shipments, energy intermediate inputs, non-energy intermediate inputs, and new capital goods; real capital stock (plant plus equipment); and nominal value of shipments.[10]

Specification

To estimate the total own-price elasticity of demand for labor for a single firm (or industry), Hamermesh proposes a specification like this.

$$(2) \qquad \ln(L) = \Sigma_i b_i \ln(w_i) + e_{it}$$

Firm demand for labor depends on all real factor prices (w_i) facing the firm, where nominal factor prices are deflated by the firm's output price (i.e., not some aggregate price index).[11] In this log-linear specification the estimated b_i for wages is the estimate of firm (or industry) j's total labor-demand elasticity, η_{LLj}. If output is included as a regressor, then the coefficient estimate for wages is the constant-output (i.e., not total) elasticity of demand for labor. This constant-output specification is as follows.

$$(3) \qquad \ln(L) = \Sigma_i b_i \ln(w_i) + \ln(Y_i) + e_{it}$$

[9]Even firm-level data sets, however, very often do not contain firm-level prices. In this case the best one can do is to merge in industry-level prices to create a hybrid data set of both firm and industry data.

[10]Payroll data do not include Social Security or employer payments for some fringe benefits. Production employees are defined as employees most directly connected with carrying out manufacturing activities of the business being reported, up to and including working foremen. Nonproduction employment counts only employees at manufacturing establishments. It excludes those employed at auxiliary/administrative establishments. The fact that only production-site nonproduction workers are reported should not affect demand estimates for production labor as long as the earnings for production-site nonproduction workers match the earnings for auxiliary-site nonproduction workers. But this should be kept in mind for the estimates of nonproduction-labor demand. Unfortunately, auxiliary-site nonproduction employment is publicly available only for Census of Manufactures years and only at the 2-digit SIC level. Because this paper works with 4-digit data, this information is too aggregated to be incorporated into the analysis.

[11]Nickell and Symons (1990) emphasize that the proper price deflator depends on what nominal factor prices are available. If there are nominal prices for only labor and capital then a value-added deflator is required. But if there are nominal prices for intermediate inputs as well then a gross-output deflator is required.

As (2) and (3) indicate, estimating industry-level labor demands requires measures of employment, real factor prices, and real output. For both labor types, employment comes directly from the data set. I construct real wages as nominal payroll per worker deflated by the shipments-price index.[12] For energy and materials, I construct real factor prices as the respective nominal price indexes divided by the shipments-price index. For capital, I construct two alternative real prices. One is nominal value added per unit of real capital deflated by the shipments-price index. The other is a Hall-Jorgensen cost-of-capital measure that multiplies the shipments-deflated price of new capital goods by a user cost which accounts for depreciation and taxes.[13] Finally, I construct real output as nominal shipments divided by the shipments-price index.

There are three specification issues to mention regarding the form of equations (2) and (3). First, both specifications assume no significant time lags between factor-price changes and firms' demand responses. If firms did respond with lags, this could be accounted for by adding lagged employment as a regressor. Hamermesh (1983) reports that typical adjustment lags are six months to one year, so in the annual data used here lags shouldn't be too important. Specifications with employment lagged one year generate results very similar to the ones actually presented below.

Second, both specifications assume that all own-price and cross-price elasticities are constant. This constant-elasticity-of-demand specification is not explicitly derived from a particular production technology. However, it is commonly used and it seems to yield plausible estimates.

Third, estimating equation (2) requires industries to have stable product-market demand. The scale effect in equation (1) measures how higher production costs reduce factor demands thanks to a reduction in the quantity of output demanded *along* a given product-demand schedule. If product demand shifts, to identify accurately the scale effect one must include demand-shift controls as additional regressors in equation (2). Unfortunately, good measures of these controls (such as capacity-utilization rates) might not exist, and without them if product-market demand is not stable then the elasticity estimates in (2) suffer omitted-variables bias. In particular, the estimates are

[12]This data set also reports hours for production workers. Results using hourly quantities and wages are very similar to the results using the annual measures, so for brevity the hourly results are not reported.

[13]I thank Jason Cummins at New York University for providing the user-cost data.

likely to be biased upwards. A positive shock to product-market demand and thus labor demand is likely to raise industry wages, either because of rent sharing or because industry factor supplies are not perfectly elastic.

Because of this potential problem of omitted-variables bias I estimate both equation (2) and equation (3). An additional benefit of estimating both equations is that if they both yield unbiased estimates, then the difference between the two own-price labor-demand elasticities is an estimate of the scale effect itself. These estimated scale effects would provide indirect evidence about product-market competitiveness.[14]

Estimation Strategy: Identification

Probably the most important estimation issue is how to identify labor demand. The identification problem in estimating equation (2) or (3) is that both labor demand and labor supply probably depend on the real wage. The ideal solution would be to estimate jointly the two schedules using instrumental variables to identify each one. In this paper I don't do this. Instead, I regress labor quantities on wages and other factor prices and interpret the coefficients as labor-demand elasticities. Thus my identifying assumption is that industry-level labor supplies are perfectly elastic. Shifts in the labor-supply schedule, as measured by movements in wages, trace out the labor-demand schedule (whose position is controlled for by the non-labor factor prices).

The main reason for not using instrumental variables is practical: the data set does not contain a good instrument for identifying labor demand. That is, the data set does not contain a variable that is plausibly included in the labor-supply equation but excluded from the labor-demand equation that can be used to shift labor supply along labor demand. Plausible non-wage determinants of labor supply are probably not the output and non-labor input prices and quantities that constitute the rest of the data set.[15]

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[14]In principle, accurate estimates of output-demand elasticities would provide direct evidence about scale effects. Unfortunately, the NBER Productivity Data Base does not seem to contain adequate information for estimating output-demand elasticities. For one thing it is not clear how large these 4-digit industries' product markets are: clearly many are part of international markets. Moreover, for many of these industries the simultaneity problem of distinguishing output supply from output demand might be quite serious.

[15]To address the simultaneity problem, lagged wages are commonly used as regressors (it is not entirely clear how this solves the problem, although the identifying assumption presumably must be that people's labor-supply decisions take time to respond to industry wages while firms' labor-demand decisions do not). This approach is not taken here because (as will be discussed) equations (2) and (3) must be estimated in time differences, not levels. Differences of logs are

Beyond the practical reason for assuming perfectly-elastic labor supplies, this assumption can be defended theoretically in at least two ways. First, Hamermesh contends that the appropriateness of identifying assumptions depends on how disaggregated the data are. Most individual firms probably face perfectly-elastic labor supplies: given exogenous wages, firms choose employment. In contrast, an entire economy probably faces perfectly-inelastic labor supply: given exogenous quantities, the economy "chooses" wages. Insofar as 4-digit SIC industries are in some sense "closer" to firms than the economy in terms of their labor-supply schedule, then this schedule is plausibly "closer" to perfectly elastic than perfectly inelastic. This approach does have the merit of having been used extensively. Almost all industry-level studies in Hamermesh's literature survey regress quantities on prices and interpret the results as labor demand only.

Second, Nickell and Symons (1990) argue that there is no identification problem because labor demand and labor supply depend on two different real wages. An industry's labor demand depends on nominal wages deflated by that industry's product price because the industry values marginal physical productivity at the industry's output price. But an industry's labor supply depends on nominal wages deflated by an aggregate consumer price index because individuals care about their real income in terms of their overall consumption basket. Thus, if the appropriate real wages are used then simultaneity should not be a problem.[16]

To summarize, this paper identifies labor demand by assuming that industry-level labor supplies are perfectly elastic. If this assumption is violated then the estimated labor-demand elasticities will be biased upwards because of the positive correlation between wages and labor supply. However, the primary concern of this paper is trends over time in elasticities rather than levels of elasticities. If the simultaneity bias in levels is relatively constant over time, then the true pattern in trends should be relatively unaffected by this bias.

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approximately growth rates, and in the data current and lagged wage growth rates are very weakly correlated--a sample correlation of just under 0.02 for both production labor and nonproduction labor. As a result, the lagged-wage regressors generate imprecise elasticity estimates that are not reported.

[16] Nickell and Symons also argue that simultaneity is not a problem so long as quantities regressed on prices generates a negative coefficient on real product wages: "The proof of the identification pudding is in the eating" (page 9). They argue that in this case it is acceptable to interpret that coefficient as a labor-demand parameter. This reasoning seems to ignore the possibility of an upward simultaneity bias which exists but which is just not large enough to generate a positive parameter estimate.

Estimation Strategy: Issues Particular to the NBER Productivity Data Base

Using the NBER Productivity Data Base involves some additional specification issues.

One important issue is that non-wage factor prices are industry-specific indexes, not actual levels. This means that there is not meaningful cross-industry variation in the level of these factor prices. But time differences in these factor prices are comparable across industries because indexes do allow cross-sectional comparisons of changes. The implication of this is that regressions which pool different industries must be run in time differences, not levels.

Time-differencing the data also controls for unobserved time-invariant industry fixed effects influencing the level of labor demand (such as production technology). However, time-differencing can also aggravate any measurement error in the regressors and result in inconsistent estimates. To minimize this inconsistency Griliches and Hausman (1986) suggest taking long differences. Accordingly, I estimate elasticities using three-year, five-year, and ten-year differences. Another advantage of longer differences is that over longer time horizons the maintained identifying assumption of perfectly-elastic labor supplies is more likely to hold. Industry-specific skills obtained on the job might tend to make industry labor supply more inelastic. Longer time horizons make this supply more elastic by allowing people more opportunity to break these industry attachments.

Another issue is that the NBER data contain measurement error. For labor, non-wage costs are not reported but they do constitute part of firms' cost for labor.[17] In addition, there is no truly "marginal" wage--just the constructed average-wage unit value. This might introduce additional measurement error if different industries employ different skill mixes within each labor group: different unit values might reflect different skill mixes rather than true differences in labor prices.[18] Hamermesh (1983) argues that the measurement error introduced by average wage measures biases

[17]Because the wage data are time-differenced for the regressions, however, this source of measurement error is probably lessened. Bosworth and Perry (1994) find that the difference in the growth of total compensation and wages has disappeared from a surprisingly small initial amount. From 1960-1973 average hourly compensation grew 0.4 percent faster per year than average wages, and since 1983 they have grown at the same rate.

[18]Alternatively, perhaps there is no measurement error and the cross-industry variation in unit values accurately reflects interindustry wage differentials. A high wage unit-value in industry X might reflect relatively high employment in this industry of more-skilled production workers. But it also might reflect the fact that that industry must pay high wages to compensate for job characteristics like a dangerous work environment. To the extent that this is the case, the calculated wage unit values might measure labor prices without skill-mix measurement error.

elasticity estimates up towards zero. But if there is measurement error in other factor prices as well then the net direction of bias is unclear.[19] Regardless of the net direction, however, as with simultaneity bias, if the measurement-error bias is relatively constant over time then the true pattern in elasticity time trends should be relatively unaffected.

One final specification issue is the proper use of the data's panel aspect. The theory described earlier envisions a single firm/industry changing its factor demands over time as international-trade conditions for that industry change over time. This implies that each of the 450 4-digit industries should be estimated separately with identification coming from each industry's time-series variation. In practice, however, this approach would entail only 34 observations (at most) per industry. With several regressors in (2) and/or (3), estimation would require pooling almost all years and would thus preclude allowing the elasticities to vary over time as is desired. This implies that allowing time-varying elasticities requires pooling industries together. The obvious cost of this is the imposed restriction that the estimated elasticities be equal across pooled industries.

The ideal tradeoff between cross-sectional and time-series pooling is not clear. In this paper I report results for two different approaches. One approach pools all 450 industries in each year. This yields annual "manufacturing-wide" elasticity estimates, but it restricts all industries to share the same elasticities. To allow some variation within manufacturing, the second approach groups the 450 industries into eight different sectors and then estimates elasticities for each sector separately year by year. Table 1 lists the eight sectors along with the number of component 4-digit SIC industries for each. Each sector groups together the 4-digit industries within some 2-digit industries, and each is chosen based on similarity of capital per worker (the ordinal ranking of which is very stable throughout the sample) and kind of output. Thus for each year, nine own-price elasticities are estimated for each kind of labor: one for all manufacturing pooled together and

[19] Clark and Freeman (1980) prove that labor-demand elasticities are still biased upwards in the case where other factor prices such as capital rentals have relatively more measurement error. Their proposed empirical solution to this problem is not to impose any restrictions on parameter estimates even if the restrictions are implied by some production technology. This actually is a reason to prefer the flexible specifications in equations (2) and (3) to a specification explicitly derived from a particular production technology.

eight for the eight different sectors. Any finer grouping of industries without offsetting time-series pooling rapidly makes parameter estimates very imprecise.[20]

In conclusion of the previous discussion, the specifications actually estimated are as follows. For both production and nonproduction labor, total and constant-output elasticities (from equations (2) and (3), respectively) are estimated annually for manufacturing overall and for each of the eight industries within manufacturing. For each specification of a labor/elasticity/year/industry combination, six regressions are estimated. Both capital-price measures are used, and time differences of three, five, and ten years are also used. All specifications are estimated using ordinary least squares with White robust standard errors to account for any cross-sectional heteroskedasticity.[21]

Empirical Results: Summary Statistics of Levels

Table 2 reports summary statistics of the estimated elasticities. For the various labor/elasticity/time-difference combinations, each row summarizes estimates across all years and all eight industries (the overall manufacturing estimates are not included). Also, Table 2 and subsequent tables report results for the user-cost capital price: results the value-added capital price are very similar and thus are suppressed for brevity.

In several ways the constant-output estimates seem very plausible and well estimated. First, for all specifications their mean lies within the range of [-0.15, -0.75] that Hamermesh (1993) proposes as plausible based on his literature survey. Second, almost all point estimates are less than zero. In none of the six cases are more than six elasticities--well under 5% of the total--estimated to be positive. Third, the large majority of the elasticity estimates are statistically significant even with White robust standard errors. In all six cases, on average about two-thirds of

[20] An earlier draft of this paper reported results from disaggregating manufacturing into the 20 2-digit SIC industries but then pooling each 2-digit industry decade by decade. The broad patterns in elasticity estimates from this earlier approach are similar to the results in this paper. But in this paper I choose more cross-sectional and less time-series pooling to generate a larger number of elasticity estimates for the stage-two regressions. The earlier approach generated only 60 elasticity estimates: 20 2-digit industries with three decades per industry. In this draft the various specifications generate from 192 estimates (using ten-year differences) up to 248 estimates (using three-year differences). The hope is that the greater number of elasticities increases the explanatory power of the stage-two regressions.

[21] For either (2) or (3), there are no cross-equation restrictions between the two equations for the two labor types that can improve efficiency by estimating the two labor demands simultaneously with the restriction(s) imposed. Given this, the two labor types are estimated separately.

the estimates are less than zero at the 5% level of significance (and none of the positive estimates are statistically significantly different from zero). Fourth, for each labor type there is a high correlation of the estimates across the three time differences. This is indicated by the closeness of the means across time differences. In addition, for each combination the sample pairwise correlations are between 0.27 and 0.52, all of which are significant beyond the 0.1% level.

In contrast to the constant-output elasticity estimates, Table 2 also reveals that the total elasticity estimates seem much less plausible. First, all six total-elasticity means are smaller (in absolute value) than their respective constant-elasticity means. This contradicts the labor-demand theory behind equation (1), which states that the reverse should be true. In addition, in all six cases somewhere between 5% and 30% of the estimates are positive while only about one third of the estimates are less than zero at the 5% level of significance. As discussed earlier, a plausible explanation for the apparent upward bias and resulting imprecision in the total-elasticity estimates is that their specifications do not control for cross-industry shifts in product demand. Without these controls, equation (2) does not capture the theoretical notion of the scale effect measuring how higher wages reduce labor demand by raising production costs and thus reducing the quantity of output demanded along a given product-demand schedule.

Although the levels of the total elasticities seem to be poorly estimated, their time trends broadly match the time trends in the constant-output elasticities. Given this, most of the subsequent empirical work focuses on the constant-output elasticities only. Unfortunately, the poor total-elasticity estimates preclude identification of changes in product-market competitiveness through the difference between the total and constant-output elasticities.

Empirical Results: Trends Over Time

Figures 1 through 9 and Tables 3 and 4 present how the estimated elasticities evolve over time.

The basic results are reported visually in the figures. First, Figures 1a and 1b plot manufacturing-wide constant-output elasticities each year for the specifications using three-year and five-year differencing. To represent better the underlying trends, the figures plot three-year moving averages of the estimated elasticities.

There is a clear difference between nonproduction and production labor. Production-labor demand became markedly more elastic. This elasticity fluctuated around -0.6 until the mid-1970s, but then it declined steadily to around -1.3 by 1990. Nonproduction-labor demand did not become more elastic. Almost all estimates somewhere between -0.5 and -0.8, and if anything, demand seemed to become less elastic over time. These patterns are very consistent across both the three-year and five-year differenced specifications (and the ten-year as well, which is omitted for readability).

Figures 2 through 9 plot three-year moving averages of both labor types from the five-year differenced specifications, each figure for one of the eight disaggregated industries.[22] These figures reveal some industrial heterogeneity not visible in the manufacturing-wide results. For production labor, demand was becoming more elastic in five industries: food and tobacco; textiles, apparel, and footwear; wood and paper products; metals; and instruments and miscellaneous. Elasticities look relatively constant in the other three industries: chemicals, petroleum, and rubber; stone, clay, glass, and transportation; and machinery. For nonproduction labor, in none of the eight industries do demand elasticities display any downward trend. If anything, demand in some of these industries seems to have grown less elastic.

So a visual inspection of the constant-output elasticities indicates an important difference between production and nonproduction labor. Production-labor demand has become more elastic over time in both manufacturing overall and in five of the eight disaggregated industries. But at no level is nonproduction-labor demand becoming more elastic. These trends actually look even stronger for the total elasticities. But as mentioned earlier, the imprecision of these total estimates makes them less reliable. For example, for production labor total elasticities show a strong downward trend--but one that starts with several years of positive elasticities before falling below zero.[23]

[22] As with Figure 1, these figures look very similar for three-year and ten-year differenced specifications. For readability only the five-year results are shown.

[23] Figures 1 through 9 also indicate that in almost all industries, for many years demand is estimated to be more elastic for nonproduction labor than for production labor. If nonproduction workers tend to be more skilled than production workers, this finding differs from the literature survey in Hamermesh (1993), where most studies find that demand becomes less elastic as the skills of a group of workers increases. One possible explanation is that the skills distributions of these two

To confirm the these visual impressions, Tables 3 and 4 report by industry time trends estimated from regressing the estimated elasticities on time. Eight trends are estimated for each industry. There are three time differences for each industry, and for each time difference three trends are estimated--one trend covering the entire sample, a second starting in 1969, and a third starting in 1975 (because the ten-year differences don't start until 1968 I do not estimate the middle trend for them). Different starting points are used to verify that the time trends are robust to their duration.

The trends in Tables 3 and 4 confirm the message of the figures for production and nonproduction labor, respectively. First, in every one of the five industries whose pictures indicate more-elastic production-labor demand, all eight estimated time trends are less than zero. And nearly three-fourths of these trends are significantly less than zero at or above the 90% level. In contrast, none of the other three industries displays a downward trend--in fact, in one industry (stone, etc./transportation) demand is becoming significantly less elastic. As for nonproduction labor, no industry shows a downward trend in elasticities. In three industries (lumber, furniture, paper, and printing; primary and fabricated metals; and machinery) at least two specifications indicate demand was becoming less elastic.

Overall, the time series of elasticities presented in the figures and tables indicate an important difference between production and nonproduction labor. Demand for production labor has become more elastic in manufacturing overall and in five of eight industries within manufacturing. But demand for nonproduction labor has not become more elastic in manufacturing overall or in any of the industries within manufacturing.[24]

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worker categories actually overlap a lot. Another is that the endogeneity problem of labor demand with labor supply is more severe for production workers. This might be the case if production workers tend to acquire more industry-specific and firm-specific skills than nonproduction workers do.

[24]These conclusions assume that over time the average quality of workers--either production or nonproduction--hired by firms does not change. If this is not the case, an alternative explanation for changes in the estimated elasticities is possible. Increasing demand elasticities might be caused by a shift in the composition of workers hired towards those with more-elastic demands--without any change over time in the elasticities for these different-quality workers. With just the NBER Productivity data I cannot rule out this possibility. But I am assuming it does not explain the trends in the estimated elasticities.

4 Stage-Two Regressions: Explaining Trends in Estimated Labor-Demand Elasticities

Specification and Data Description

The issue now is to explain what caused changes in labor-demand elasticities. One approach to doing this is to solve a well-specified general-equilibrium model for labor-demand elasticities in terms of exogenous variables, some of which are presumably trade-related such as trade policies and transportation costs. This would generate one or more structural equations to be estimated. An alternative approach is to estimate a reduced-form equation of estimated elasticities on a set of explanatory regressors which are both plausible and hopefully exogenous in the implicit structural model.

I adopt the second approach because it is not clear what single trade model is most appropriate. To explain the estimated elasticities I use the following reduced-form regression.

$$\text{(4)} \qquad (PED)_{it} = a + \Sigma_j b_j(\text{exogenous factors}_{ijt}) + \Sigma_i \gamma_i(ID_i) + \Sigma_t \delta_t(TD_t) + e_{it} \ .$$

In equation (4), $(PED)_{it}$ is a set of elasticities estimated from a particular specification in stage one for I industries over T years; there are J different (hopefully) exogenous factors that vary by industry-year to explain the elasticities; ID_i is a full set of industry dummies; and TD_t is a full set of time dummies. Industry dummies control for industry-specific time-invariant level differences in elasticities that are not accounted for by the J regressors (e.g., industry-specific technology). Time dummies control for industry-shared time-varying level differences in the elasticities that are not accounted for by the J regressors (e.g., skill-biased technological change). I also try specifications replacing the time dummies with a more-restrictive time trend to see if time's effect on the elasticities can be adequately summarized with just a trend.

The set of J exogenous factors should include measures of (at least) international trade, technology, and labor-market institutions. Other relevant factors (e.g., U.S. antitrust policy affecting product-market competitiveness) are hopefully controlled for by the industry and time dummies.

Table 5 lists summary statistics for 14 different explanatory variables used in equation (4).[25] There are ten trade measures, three technology measures, and one measure of labor-market institutions. Most of these variables have been used in recent studies of rising U.S. wage inequality. This makes them plausible variables for explaining labor-demand elasticities. Moreover, their previous use has the practical advantage of making them easily accessible.

All variables are constructed to match the industry-year panel of the estimated elasticities. In addition to the summary statistics, the table also lists each variable's hypothesized effect on the estimated elasticities for both production and nonproduction labor. Because the estimated elasticities are (almost all) less than zero, a hypothesized positive effect means that an increase in the regressor should make labor demand less elastic (i.e., make the elasticity less negative by increasing the elasticity closer to zero). Similarly, a hypothesized negative effect means that an increase in the regressor should make labor demand more elastic (i.e., make the elasticity more negative by reducing the elasticity farther from zero).

Here is a summary of each variable's definition, data source, and hypothesized effect on the elasticities. Additional data information is included in the short appendix.

- Trade measure #1: transportation costs, Feenstra (1996). These are constructed as the ratio of c.i.f. (cost, insurance, and freight) import value to customs import value. Declining transportation costs should make international product markets more competitive; this should make all factor demands more elastic via the scale effect.
- Trade measure #2: U.S. share of world value added, United Nations (1996). This is an alternative measure of how competitive international product-markets are. The more the rest of the world accounts for an industry's worldwide output, the more likely it is that that industry is more competitive for U.S. firms and thus the more elastic all factor demands will be via the scale effect.

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[25] I thank Gordon Hanson of the University of Texas for providing me with some of these data.

- Trade measure #3: percentage change in U.S. producer prices, NBER (1997). The assumption here is that larger price increases signal less price competition in output markets and thus less-elastic factor demands via the scale effect.
- Trade measure #4: percentage change in U.S. producer prices less percentage change in total-factor productivity (tfp), NBER (1997). Following Leamer (1996), these "adjusted" price changes assume that any tfp growth passes through 100% to reduced prices. The residual price change is assumed to be the price change attributable to globalization. Its effect on factor demand is as in measure #3.
- Trade measure #5: outsourcing broadly measured, Feenstra and Hanson (1997). This measures the share of all intermediate inputs that are imported. Increased outsourcing is assumed to make demand more (less) elastic for production (nonproduction) labor via the substitution effect. Foreign outsourcing provides an alternative to many production-labor-intensive activities done in the U.S. but also increases reliance on U.S. nonproduction labor (in part to coordinate the outsourced activities).
- Trade measure #6: outsourcing narrowly measured, Feenstra and Hanson (1997). This measures only intermediate inputs imported in the same 2-digit SIC industry as the importer. Its effect on labor demand is as in measure #5.
- Trade measure #7: foreign-affiliate share of U.S. multinationals' total assets, U.S. Department of Commerce (various years). This is a more narrow measure of outsourcing in that it looks only at within-firm activity done by U.S.-headquartered multinationals. Its effect on labor demand is as in measure #5.
- Trade measure #8: foreign-affiliate share of U.S. multinationals' total employment, U.S. Department of Commerce (various years). This is another more narrow measure of outsourcing. Its effect on labor demand is as in measure #5.
- Trade measure #9: ratio of imports to shipments, Feenstra (1996). This is another possible measure of the competitiveness of product markets. The assumption is that more import

penetration signals more competition. This makes all factor demands more elastic via the scale effect.

- Trade measure #10: ratio of net-exports to shipments, Feenstra (1996). This is another possible measure of the competitiveness of product markets. The assumption is that higher net exports signals less foreign competition. This makes all factor demands less elastic via the scale effect.
- Technology measure #1: percentage change in total-factor productivity (tfp), NBER (1997). It is assumed that higher tfp growth represents technological change which makes production labor more substitutable with the new technology but which increases reliance on nonproduction labor. This changes factor demands differentially through the substitution effect.
- Technology measure #2: share of computers in total capital stock, Berndt and Morrison (1995). The assumption here is that more computers make production labor more substitutable but nonproduction labor less so. This changes factor demands differentially through the substitution effect.
- Technology measure #3: share in total capital stock of computers plus other "high-tech" equipment, Berndt and Morrison (1995). Its effect on labor demand is assumed to be the same as for the previous technology measure.
- Labor-market institutions measure #1: percentage of production workers unionized, Abowd (1991). Greater unionization is assumed to make production-labor demand less elastic. Its predicted effect on nonproduction-labor demand is not clear, so this relationship is not tested.

Estimation Strategy

There are three issues to mention regarding the estimation strategy. One is the exogeneity of the regressors. It is likely that many of them are endogenous variables in a fully-specified model. For example, all four outsourcing measures and the two capital-stock measures are input quantities endogenously chosen by firms. In addition, within a fully-specified trade model imports and net exports are endogenous outcomes of consumption and production decisions. In contrast, the two most plausibly exogenous trade measures are transportation costs and the U.S. share of world value added. If some regressors are endogenous, then least-squares parameter estimates will suffer endogeneity bias, the net direction of which is not clear. Despite this potential problem, for lack of valid instruments I use least squares.[26]

A second issue is the fact that the dependent variable in equation (4) is estimated, not observed. This means that the error term e_{it} in (4) is heteroskedastic with mean zero and additive variance equal to the variance of the error term of the stage-one regression plus the variance of the estimated elasticity PED_{it}. Controlling for the heteroskedasticity requires weighting less heavily observations whose elasticities that are relatively imprecisely estimated. To do this, following Anderson (1993) I proceed as follows. First I run equation (4) using OLS. Next I use the squared residuals from this equation as the dependent variable regressed on the estimated variances of the elasticities along with the these variances squared and cubed. I then construct the predicted values of this regression: these tell the amount of the original squared residuals "explained" by the variance of the elasticities. Finally, the inverses of these predicted values are constructed to be used as weights for weighted-least squares estimation of (4).

A third issue is what regressors to include in equation (4). Without a structural equation neither the appropriate regressors nor their functional form is clear. To ensure the robustness of the results I first used each of the 14 explanatory factors individually. I then reestimated equation (4) using all possible combinations of two regressors, each from a different broad category (trade, technology, and institutions), and then using all possible combinations of three regressors, each from a different category. The overall results are not sensitive to the exact specification. Also, to understand the explanatory power of the industry and time controls, for each set of exogenous factors I estimated (4) first with no controls and then with the different possible combinations of controls: just industry dummies, just time dummies (or a time trend), and both industry dummies and time dummies (or a time trend).

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[26]To control for endogeneity I tried using regressors lagged one year (where possible) instead of contemporaneous regressors. The results were similar either way, so for brevity the lagged results are not reported here.

In summary, to explain the stage-one elasticity estimates, in stage two I estimate equation (4) using as regressands all the various sets of elasticity estimates. I use weighted least squares to control for heteroskedasticity generated from using estimated regressands, and as regressors I try different combinations of exogenous factors, industry controls, and time controls.[27]

Empirical Results

Table 6 reports estimation results for production labor and Table 7 for nonproduction labor. The results are from specifications using five-year constant-output elasticities as regressands and using only a single exogenous factor as a regressor. For brevity I report only one representative set of results for each labor type. Many other specifications were run using other estimated elasticities as regressands and using multiple exogenous factors as regressors. In addition, because the proper specification for equation (4) is not clear, I also tried some specifications with changes in elasticities (both level and percentage) as regressands. The overall results were robust to these different specifications. In particular, results were quite similar between comparable constant-output and total elasticities. In theory, because of the scale-effect difference between the two this need not be the case. But in the data these elasticities are sufficiently correlated to yield similar results. Because of this, Tables 6 and 7 report results for constant-output elasticities even though some regressors in theory influence the scale effect.

For production labor, the main message of Table 6 is that time fixed effects dominate the explanatory power of most of the trade and technology measures. Eight of the 14 measures (product prices; product prices less tfp growth; broad and narrow outsourcing; imports and net exports as a share of shipments; and computers and high-tech capital as a share of total capital) have the correct hypothesized sign and a t-statistic of at least one (in absolute value) with both no controls and industry fixed effects. And an additional three (transportation costs; U.S. value-added share; and U.S. affiliate asset shares) have the correctly predicted sign with t-statistics near

[27]It has been suggested that instead of doing the empirical work in two stages I might combine them somehow into just one stage. I have not done this because it is not clear that regressing labor quantities on factor prices plus measures of trade, technology, and institutions would actually identify labor-demand elasticities. Although the stage-one regressions are not trouble-free (as discussed earlier), they certainly are closer to the underlying labor-demand theory than any composite specification would be.

or above one when industry fixed-effects are included. But for all 11 of these controls time dummies either reduce the parameter estimates to insignificantly different from zero or even make them statistically significant but opposite of the hypothesized sign. Only one regressor, tfp growth, has relatively stable estimates across all combination of controls. U.S. affiliate employment shares have the wrong sign throughout, and unionization is not robust to the inclusion of industry fixed effects.

This dominance of the time effects appears to be driven by the fact that the regressors do not contain enough cross-sectional variation over time that is independent of time itself to explain the elasticities as predicted. Scatterplots by industry of each regressor against time make this point quite clearly. Nine of the 11 regressors "dominated" by time look remarkably similar over time across industries. This is true for seven of the trade variables. The two outsourcing measures, import penetration, and U.S. affiliate assets are all increasing in every industry while transportation costs, U.S. value added, and net exports are all declining in every industry (with the exception of food for net exports). For the technology variables, the computer and high-tech variables are increasing in every industry.[28]

When a single time trend is used instead of year dummies, in almost all specifications this time trend has a negative coefficient significantly different from zero at at least the 5% level. The robustness of this time trend suggests that time's effect can reasonably thought of as a force constantly making product demand more elastic over time.

The results for nonproduction labor are not quite as dominated by time. Six of the 13 regressors (both outsourcing measures; both multinational measures; net exports as a share of shipments; and tfp growth) actually have the same correctly predicted sign across all combination of controls. And four of these (both outsourcing measures; MNC assets; and net exports) have coefficients significant at at least the 90% level for the full-control specification. One regressor, imports as a share of shipments, obtains the correctly predicted sign--but not significantly different from zero--when time effects are included. Only two regressors, computers and high-tech capital,

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[28]The dominance of time is not as clearly visible for product prices and product prices adjusted for tfp.

have correctly predicted signs near the 90% level of significance with industry dummies but then have time effects reduce these estimates to insignificantly negative. The remaining four regressors are either insignificant or incorrectly predicted across the various specifications.

In contrast to the results for production labor, here many regressors do seem to have enough cross-industry variation over time that is independent of time itself to explain as predicted some of the variation in estimated elasticities. But as with production labor, when time's effect is captured with a time trend instead of time dummies it has a significant effect in almost all specifications. Now, however, the estimated coefficient is positive, not negative. As was seen in the stage-one regressions, nonproduction-labor demand becomes progressively less elastic.

Overall, the results in Tables 6 and 7 provide mixed support, at best, for the hypothesis that international trade has contributed to changes in U.S. labor-demand elasticities. For production labor many trade variables have the predicted effect for specifications with only industry controls, but these predicted effects disappear when time controls are included as well. For nonproduction labor things are somewhat better. Four plausible trade variables have the predicted sign at at least the 90% level of significance when both industry and time controls are included. For both labor types time is a very strong predictor of elasticity patterns with production (nonproduction) demand becoming progressively more (less) elastic over time.

Discussion of Empirical Results

There are three issues related to these results worth briefly discussing. One is that the three regressors--the two outsourcing measures and the multinational-asset measure--which seem most robust across both labor types are regressors which predict a differential effect between the two labor types. This squares with the stage-one finding that the predominant forces on U.S. labor-demand elasticities are affecting production and nonproduction labor differently. Product-market developments and their implicit scale effects cannot be the main force because within industries scale effects move all factor demands in the same direction. Instead, forces differentially changing labor substitutability must be playing a major role. The stage-two results provide some evidence that trade is doing this by making production labor more easily substituted for foreign factors of production.

A second issue is the endogeneity of many of the trade regressors. Three of the four trade variables that "work" for nonproduction labor are endogenous quantities chosen by firms. In general, endogeneity might help explain the weak results, and obtaining better--i.e., exogenous--regressors might improve things. However, it is not clear that this alone would be sufficient. Transportation costs, the trade regressor that seems most plausibly exogenous to firms and consumers, is insignificant in the full specification for nonproduction labor and actually significant but with the wrong sign in the full specification for production labor. Exogeneity alone does not seem sufficient without adequate cross-industry variation over time as well.

One major problem with the trade measures might be that it is not actual trade that matters but rather potential trade. That is, what might matter for labor demand is just the ability to transact internationally regardless of whether such transactions actually occur. Product markets might become more competitive from increased contact with foreign producers even if product-market prices or quantities don't change. Similarly, factor substitutability might increase from easier access to foreign factors of production even if firms do not actually do this. Thus trade might be playing a large role without any change in econometric observables such as output prices, quantities, trade flows, and foreign-direct investment flows.[29]

The final issue, how to interpret time's role in explaining elasticities, is related to these measurement problems. Again, in the full specification with time fixed effects transportation costs (and lots of other regressors) have the incorrect sign at least partly because they have insufficient cross-industry variation over time that is independent of time itself to explain the elasticities in the predicted way. The time controls are appropriate regressors if the other included regressors do not account for all time-varying factors influencing elasticities. Unfortunately, because equation (4) is a reduced-form equation this issue cannot be unambiguously resolved. This raises the question of

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[29]In contrast, many of the channels through which trade affects factor prices do necessarily involve changes in econometric observables. For example, in standard Heckscher-Ohlin models, for the Stolper-Samuelson process to affect relative factor prices, relative product prices must first change.

whether time's role can justifiably be attributed to trade, technology, or other factors. For example, perhaps trade's true effect is to increase its "threat" over time--both in terms of product-market competitiveness and factor substitutability--independent of actual changes in econometric observables. This might be a reason to attribute time's explanatory power to trade. On the other hand, perhaps computerization's true effect is a similar "threat" independent of whether computers are actually used. In this case perhaps time should be attributed to technology. It is not obvious how to distinguish among these alternatives.

The role of time seems to parallel the common finding that observed measures of trade and/or technology explain only a minority of rising wage inequality. Just as there appears to be a large unexplained residual for changing factor prices, there also appears to be a large unexplained residual for changing factor demand elasticities.

6 Conclusion

The goal of this paper has been to determine whether international trade has increased U.S. firms' equilibrium own-price elasticity of demand for labor.

The paper has three main results. First, over time demand for production labor has become more elastic in manufacturing overall and in five of eight industries within manufacturing. The elasticity fluctuated around -0.6 until the mid-1970s, but then it dropped steadily to around -1.3 by 1990. Second, nonproduction-labor demand has not become more elastic in manufacturing overall or in any of the industries within manufacturing. Almost all estimates range somewhere between -0.5 and -0.8, and if anything, demand seems to be growing less elastic over time.

Third, the hypothesis that trade contributed to increased elasticities has mixed support, at best. For production labor many trade variables have the predicted effect for specifications containing as regressors only these variables or them plus industry fixed effects. However, these predicted effects generally disappear when time controls are included as well. For nonproduction labor things are somewhat better. Four plausible trade variables--narrow and broad outsourcing, the foreign-affiliate share of U.S. multinational corporations' assets, and net exports as a share of shipments--have the predicted sign at at least the 90% level of significance even when both industry and time controls are included. For both labor types time is a very strong predictor of elasticity patterns, with production (nonproduction) demand becoming progressively more (less) elastic.

This result parallels the common finding in studies of wage inequality that measures of trade and/or technology explain only a minority of wage patterns. Just as there appears to be a large unexplained residual for changing factor prices, there also appears to be a large unexplained residual for changing factor demand elasticities.

Data Appendix

This appendix provides some additional information about the data used in the stage-two regressions.

For trade variable #1 (transportation costs) the necessary import value data go back only to 1974. For trade variable #2 (U.S. share of world value added) the original United Nations data start in only 1963 and they are reported by ISIC manufacturing industries. These are concorded up to the eight industries used in this paper. For trade variables #2 and #3 (percentage change in product prices and percentage change in product prices less tfp) and for technology variable #1 (percentage change in tfp), the original data are for 4-digit SIC industry/year observations. These are aggregated up to the appropriate industry-years using the value of shipments as weights. For both outsourcing variables (trade measures #5 and #6) and for the remaining two technology variables, the data are available for only three years: 1972, 1979, and 1990. Also, these data are originally at the 4-digit SIC level; they are aggregated up using the value of shipments as weights. For the multinational variables (trade measures #7 and #8) the data are available only for 1977 and 1982 forward. For assets, the publicly available data are suppressed in 1985 and 1986 for the U.S. parents in the industry "miscellaneous." Finally, the unionization variable (institution measure #1) is reported in Abowd (1991) for only three years: 1974, 1980, and 1984. In all instances of weighting original data to generate data for the eight sectors used in this paper, very similar results are obtained using alternative weights such as value added or employment.

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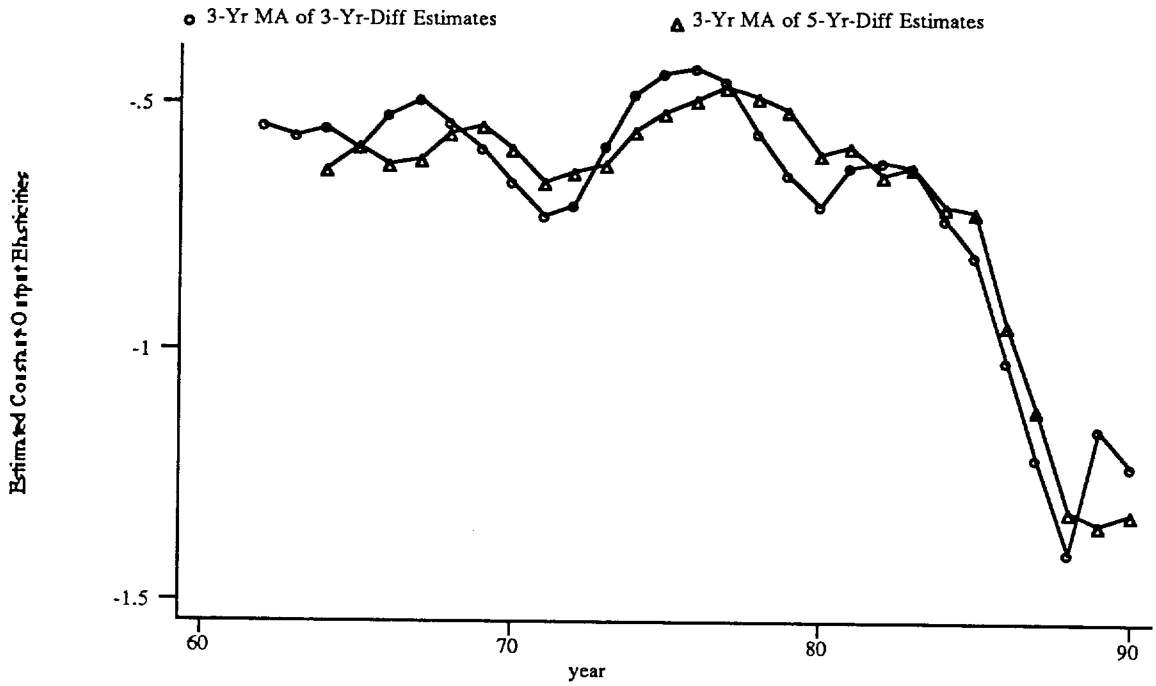

Figure 1a: Production-Labor-Demand Elasticities, All Manufacturing

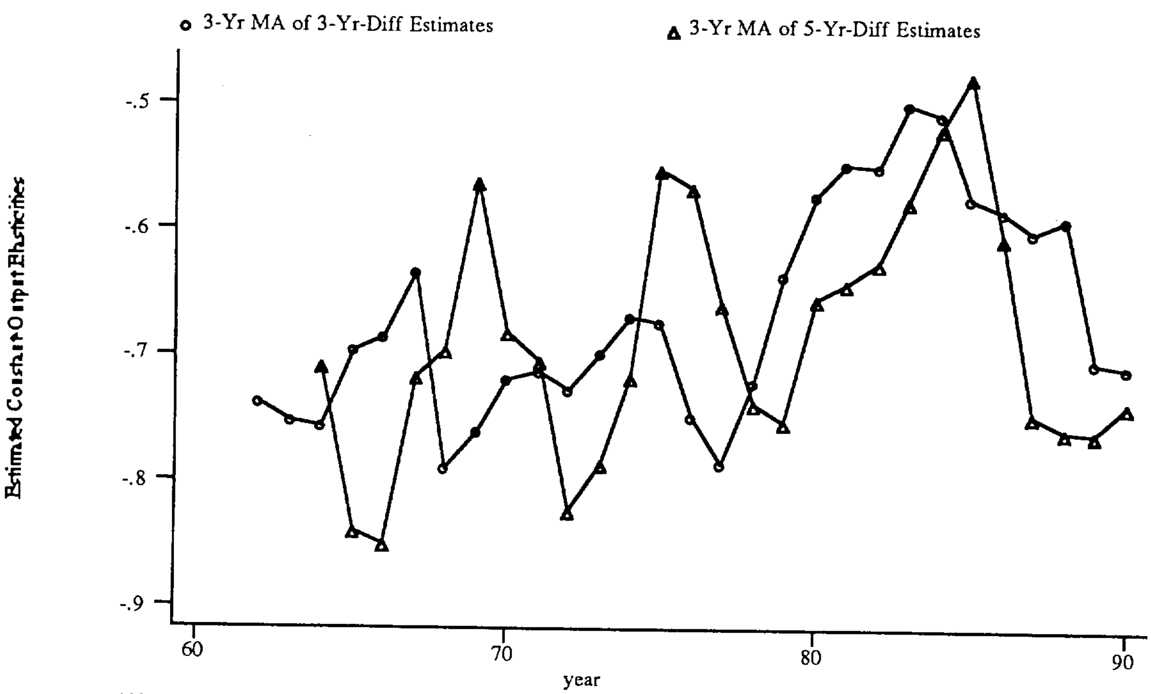

Figure 1b: Nonproduction-Labor-Demand Elasticities, All Manufacturing

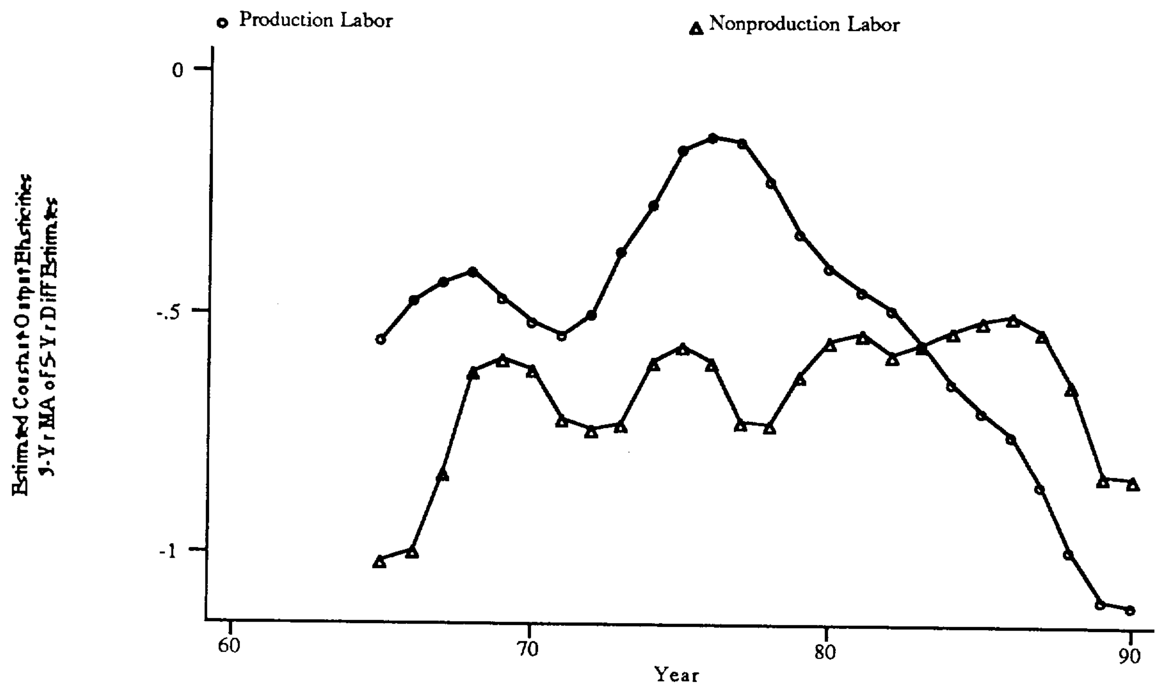

Figure 2: Labor-Demand Elasticities for Food and Tobacco

Figure 3: Labor-Demand Elasticities for Textiles, Apparel, Footwear

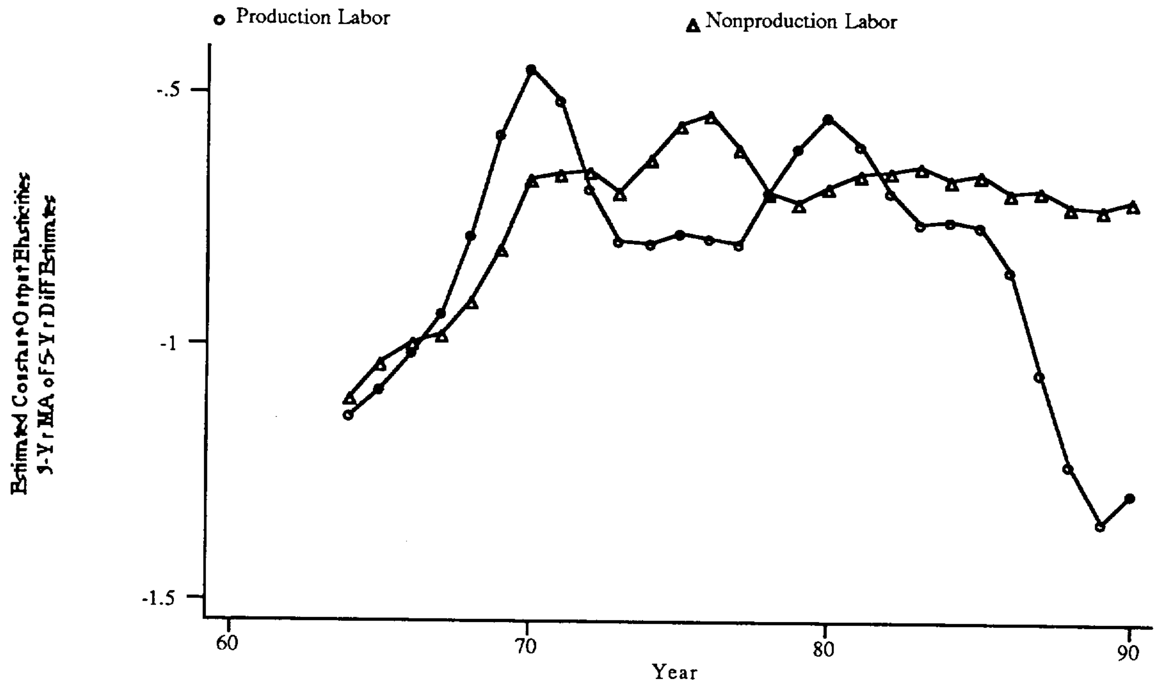

Figure 4: Labor-Demand Elasticities for Wood, Paper, Printing

Figure 5: Labor-Demand Elasticities for Chemicals, Petroleum, Rubber

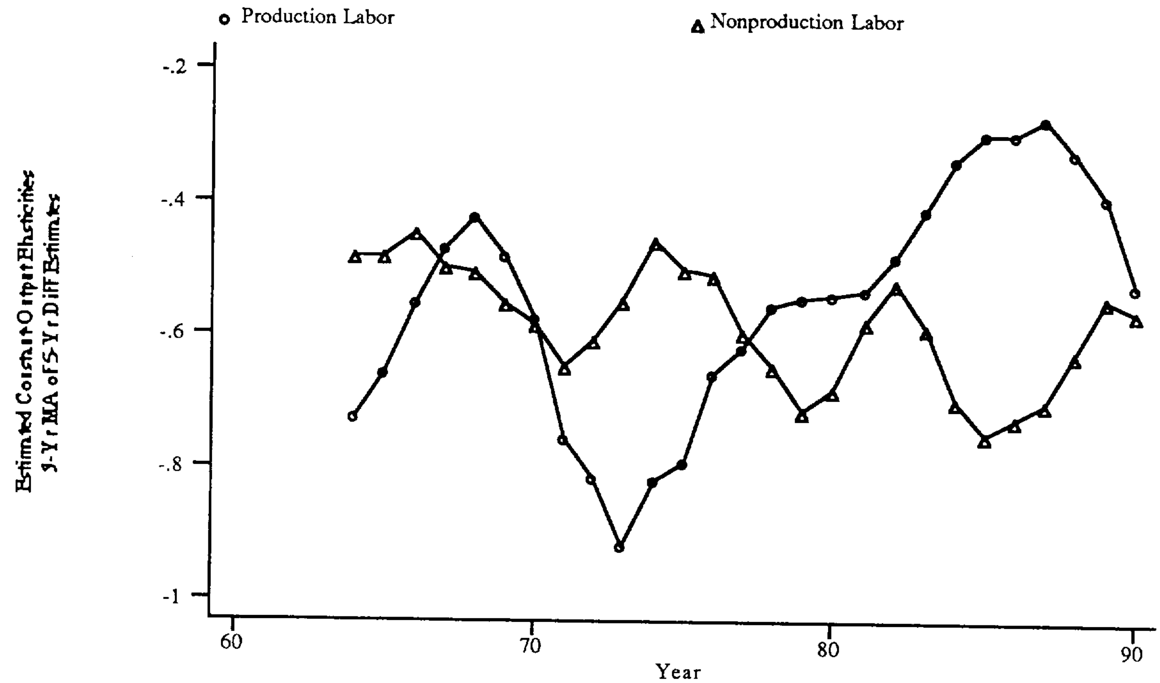

Figure 6: Labor-Demand Elasticities for Stone, Glass; Transportation

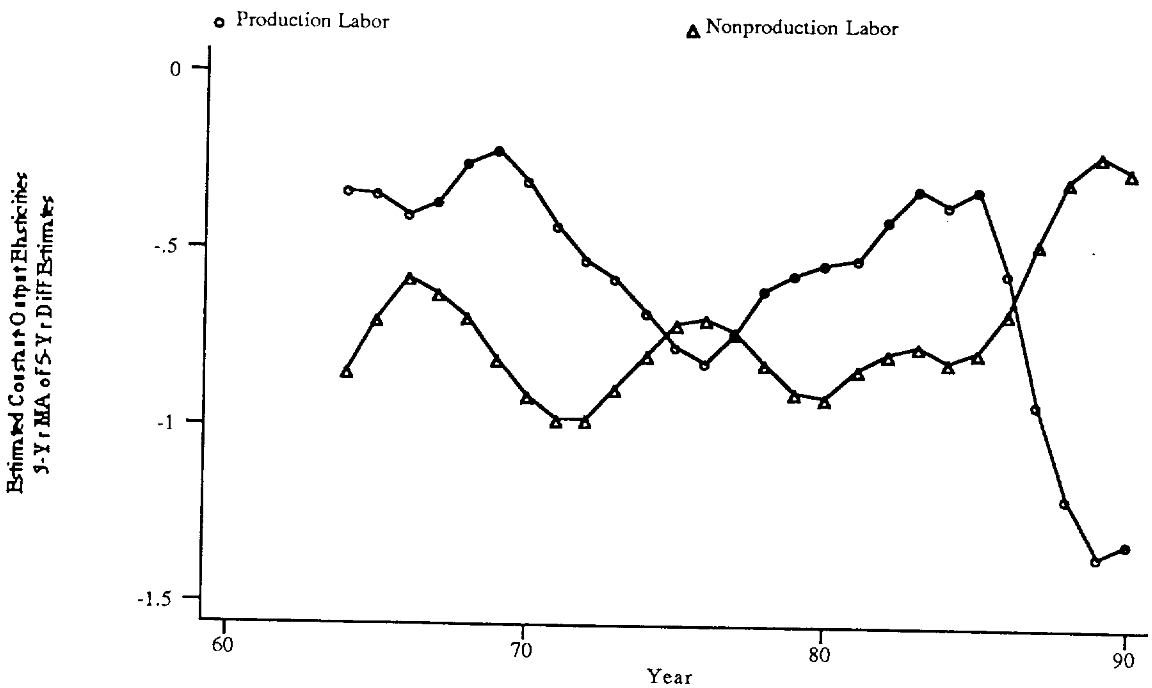

Figure 7: Labor-Demand Elasticities for Primary & Fabricated Metals

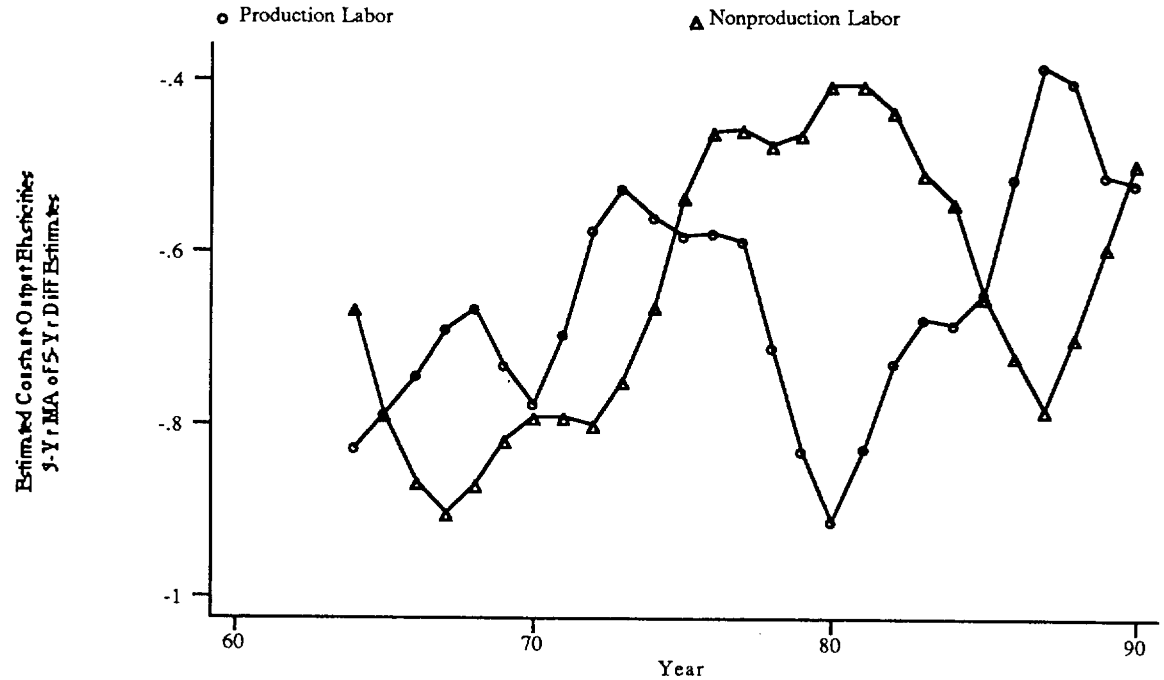

Figure 8: Labor-Demand Elasticities for Machinery

Figure 9: Labor-Demand Elasticities for Instruments & Miscellaneous

Table 1

Industry Numbers and Names

Aggregated Industry	Component SIC Industries	Annual Number of 4-Digit Industries	Component-Industry Description
1	20, 21	51	Food and Tobacco
2	22, 23, 31	74	Textiles, Apparel, and Footwear
3	24, 25, 25, 27	64	Lumber, Furniture, Paper, and Printing
4	28, 29, 30	39	Chemicals, Petro-leum, and Rubber
5	32, 37	44	Stone, Clay, Glass; Transportation Products
6	33, 34	62	Primary Metals and Fabricated Metals
7	35, 36	84	Nonelectical Machinery and Electrical Machinery
8	38, 39	33	Instruments and Miscellaneous Products

Table 2

Own-Price Labor-Demand Elasticities
Summary Statistics

Labor Type	Elasticity	Time Diff.	# Obs.	Mean	Std. Dev.	Minimum	Maximum
Nonproduction	Constant-Output	10 years	192	-0.70	0.28	-1.44	0.08
	Total		192	-0.58	0.49	-2.24	1.28
	Constant-Output	5 years	232	-0.68	0.27	-1.36	-0.03
	Total		232	-0.59	0.38	-1.58	0.52
	Constant-Output	3 years	248	-0.70	0.24	-1.34	0.03
	Total		248	-0.63	0.31	-1.35	0.22
Production	Constant-Output	10 years	192	-0.63	0.31	-1.67	0.02
	Total		192	-0.24	0.63	-2.15	1.66
	Constant-Output	5 years	232	-0.65	0.34	-1.75	0.11
	Total		232	-0.36	0.56	-2.15	0.96
	Constant-Output	3 years	248	-0.65	0.34	-2.04	0.22
	Total		248	-0.43	0.53	-2.42	1.05

Total and constant-output elasticities are from specifications described in equations (2) and (3).
These statistics summarize only the eight disaggregated industries.
They do not include estimates for all manufacturing pooled together.

Table 3
Time Trends in Constant-Output Own-Price
Labor-Demand Elasticities for Production Labor

Industry	Specification (Time Differences)	All Years	1969 Forward	1975 Forward
Food &	Three-Year	-0.011**	-0.026***	-0.036***
Tobacco		(0.005)	(0.006)	(0.009)
	Five-Year	-0.017**	-0.033***	-0.071***
		(0.006)	(0.008)	(0.006)
	Ten-Year	-0.026***		-0.037***
		(0.006)		(0.008)
Textiles,	Three-Year	-0.013**	-0.001	-0.001
Apparel,		(0.005)	(0.004)	(0.009)
Footwear	Five-Year	-0.011**	-0.008	-0.003
		(0.005)	(0.008)	(0.013)
	Ten-Year	-0.014*		-0.040***
		(0.008)		(0.010)
Lumber,	Three-Year	-0.010*	-0.022**	-0.011
Furniture,		(0.006)	(0.008)	(0.011)
Paper,	Five-Year	-0.008	-0.034***	-0.047***
Printing		(0.007)	(0.009)	(0.013)
	Ten-Year	-0.006		-0.009
		(0.010)		(0.011)
Chemicals,	Three-Year	0.004	0.003	-0.008
Petroleum,		(0.006)	(0.010)	(0.017)
Rubber	Five-Year	0.004	-0.003	-0.015
		(0.007)	(0.009)	(0.014)
	Ten-Year	0.002		0.015
		(0.008)		(0.013)

All time trends generated from regressing the specified set of estimated elasticites on time.
Standard errors are in parentheses.
***, **, and * denote significance at the 99%, 95%, and 90% levels.

Table 3
Time Trends in Constant-Output Own-Price
Labor-Demand Elasticities for Production Labor

Industry	Specification (Time Differences)	All Years	1969 Forward	1975 Forward
Stone, etc.;	Three-Year	0.004	0.025*	0.003
Transportation		(0.008)	(0.013)	(0.017)
	Five-Year	0.013**	0.018**	0.018
		(0.006)	(0.009)	(0.011)
	Ten-Year	0.022***		0.047***
		(0.007)		(0.010)
Primary &	Three-Year	-0.023***	-0.015	-0.035*
Fabricated Metals		(0.007)	(0.011)	(0.019)
	Five-Year	-0.027***	-0.032**	-0.038*
		(0.008)	(0.012)	(0.022)
	Ten-Year	-0.023***		-0.014
		(0.008)		(0.014)
Machinery	Three-Year	0.008	0.009	0.025
		(0.006)	(0.009)	-0.016
	Five-Year	0.007	0.007	0.011
		(0.006)	(0.009)	(0.013)
	Ten-Year	0.005		0.010
		(0.006)		(0.010)
Instruments &	Three-Year	-0.015*	-0.033**	-0.034
Miscellaneous		(0.009)	(0.015)	(0.027)
	Five-Year	-0.022**	-0.037***	-0.083***
		(0.009)	(0.013)	(0.020)
	Ten-Year	-0.021**		-0.035**
		(0.009)		(0.013)

All time trends generated from regressing the specified set of estimated elasticites on time.
Standard errors are in parentheses.
***, **, and * denote significance at the 99%, 95%, and 90% levels.

Table 4
Time Trends in Constant-Output Own-Price
Labor-Demand Elasticities for Nonproduction Labor

Industry	Specification (Time Differences)	All Years	1969 Forward	1975 Forward
Food &	Three-Year	0.000	-0.003	-0.009
Tobacco		(0.006)	(0.008)	(0.012)
	Five-Year	0.001	-0.006	-0.019
		(0.008)	(0.009)	(0.014)
	Ten-Year	0.001		-0.001
		(0.007)		(0.008)
Textiles,	Three-Year	0.003	0.004	0.011
Apparel,		(0.004)	(0.007)	(0.013)
Footwear	Five-Year	0.000	0.003	0.010
		(0.005)	(0.008)	(0.012)
	Ten-Year	-0.015		-0.020*
		(0.012)		(0.011)
Lumber,	Three-Year	0.012***	0.008	0.003
Furniture,		(0.004)	(0.006)	(0.010)
Paper,	Five-Year	0.012**	0.003	-0.009
Printing		(0.005)	(0.006)	(0.009)
	Ten-Year	0.012		-0.015
		(0.012)		(0.011)
Chemicals,	Three-Year	0.004	0.000	0.016
Petroleum,		(0.005)	(0.008)	(0.013)
Rubber	Five-Year	-0.001	-0.001	0.012
		(0.007)	(0.011)	(0.017)
	Ten-Year	-0.015		-0.006
		(0.009)		(0.008)

All time trends generated from regressing the specified set of estimated elasticities of time.
Standard errors are in parentheses.
***, **, and * denote significance at the 99%, 95%, and 90% levels.

Table 4
Time Trends in Constant-Output Own-Price
Labor-Demand Elasticities for Nonproduction Labor

Industry	Specification (Time Differences)	All Years	1969 Forward	1975 Forward
Stone, etc.;	Three-Year	-0.007	-0.007	0.001
Transportation		(0.005)	(0.008)	(0.011)
	Five-Year	-0.006	-0.004	0.001
		(0.006)	(0.008)	(0.014)
	Ten-Year	-0.006		-0.006
		(0.009)		(0.010)
Primary &	Three-Year	0.011*	0.027***	0.055***
Fabricated Metals		(0.006)	(0.009)	(0.013)
	Five-Year	0.016***	0.029***	0.036**
		(0.006)	(0.007)	(0.012)
	Ten-Year	0.005		0.014
		(0.007)		(0.013)
Machinery	Three-Year	0.010**	0.000	-0.016
		(0.004)	(0.006)	(0.0010)
	Five-Year	0.011**	0.008	-0.014
		(0.004)	(0.006)	(0.009)
	Ten-Year	0.006		0.007
		(0.006)		(0.010)
Instruments &	Three-Year	0.003	0.003	-0.003
Miscellaneous		(0.004)	(0.006)	(0.010)
	Five-Year	0.001	0.001	-0.019
		(0.005)	(0.008)	(0.012)
	Ten-Year	0.005		-0.035
		(0.012)		(0.028)

All time trends generated from regressing the specified set of estimated elasticities of time.
Standard errors are in parentheses.
***, **, and * denote significance at the 99%, 95%, and 90% levels.

Table 5

Stage-Two Regressors
Summary Statistics

Explanatory Variable	Number of Observations	Sample Mean	Sample Std. Dev.	Sample Minimum	Sample Maximum	Hypothesized Effect on P	Hypothesized Effect on NP
Transportation Costs	144	1.06	0.02	1.02	1.10	B > 0	B > 0
U.S. Share of World Value Added	232	0.36	0.16	0.03	0.72	B > 0	B > 0
% Change in Domestic Prices	264	0.04	0.05	-0.11	0.37	B > 0	B > 0
% Change in (Prices-TFP)	264	0.03	0.06	-0.12	0.43	B > 0	B > 0
Outsourcing Broad	24	0.09	0.05	0.02	0.20	B < 0	B > 0
Outsourcing Narrow	24	0.03	0.02	0.00	0.09	B < 0	B > 0
Affiliate Share of U.S. MNC Assets	78	0.20	0.05	0.12	0.33	B < 0	B > 0
Affiliate Share of U.S. MNC Empl	80	0.27	0.06	0.14	0.37	B < 0	B > 0
Imports/ Shipments	264	0.09	0.07	0.01	0.32	B < 0	B < 0
Net Exports/ Shipments	264	-0.02	0.06	-0.26	0.09	B > 0	B > 0
% Change in TFP	264	0.01	0.02	-0.08	0.07	B < 0	B > 0
Computer Share of Total K Stock	24	0.01	0.02	0.00	0.07	B < 0	B > 0
High-Tech Share of Total K Stock	24	0.04	0.04	0.00	0.13	B < 0	B > 0
% Production Workers Unionized	24	0.40	0.15	0.20	0.68	B > 0	N.A.

Stage-two regressions run estimated labor-demand elasticities on these regressors.
The final two columns report the hypothesized effect of each regressor
on production and nonproduction elasticities, respectively.

Table 6

Stage-Two Regression Results
Explaining Production-Labor-Demand Elasticities
Estimated Parameters and (t-statistics)

Explanatory Variable	Hypothesized Effect on P	No Controls	Industry Fixed Effects	Time Fixed Effects	Industry & Time Fixed Effects	# of Observations
Transportation Costs	B > 0	-0.657 (-0.461)	2.790 (0.925)	-1.708 (-1.201)	-7.488 (-2.108)	144
U.S. Share of World Value Added	B > 0	-0.215 (-1.552)	0.325 (1.262)	-0.494 (-3.302)	-0.879 (-1.419)	232
% Change in Domestic Prices	B > 0	0.620 (1.506)	0.562 (1.381)	0.389 (0.597)	-0.082 (-0.128)	264
% Change in (Prices-TFP)	B > 0	0.511 (1.532)	0.472 (1.431)	0.430 (0.861)	0.139 (0.282)	264
Outsourcing Broad	B < 0	-2.293 (-2.851)	-3.438 (-2.080)	0.473 (0.452)	2.434 (1.227)	24
Outsourcing Narrow	B < 0	-4.486 (-1.685)	-4.553 (-1.267)	2.747 (1.692)	5.098 (1.490)	24
Affiliate Share of U.S. MNC Assets	B < 0	1.296 (1.312)	-1.735 (-0.992)	2.056 (2.083)	-0.001 (-0.001)	78
Affiliate Share of U.S. MNC Empl	B < 0	2.103 (2.833)	0.717 (0.505)	2.153 (2.982)	0.740 (0.531)	80
Imports/ Shipments	B < 0	-0.641 (-2.112)	-0.471 (-1.297)	0.314 (0.778)	1.636 (2.959)	264
Net Exports/ Shipments	B > 0	0.606 (1.643)	0.475 (1.002)	0.054 (0.127)	-1.426 (-2.264)	264
% Change in TFP	B < 0	-0.985 (-0.959)	-0.964 (-0.950)	-1.460 (-1.090)	-1.318 (-1.012)	264
Computer Share of Total K Stock	B < 0	-8.413 (-2.435)	-9.863 (-2.534)	3.024 (1.391)	1.798 (0.394)	24
High-Tech Share of Total K Stock	B < 0	-3.373 (-2.211)	-4.619 (-2.765)	4.101 (2.319)	1.991 (0.760)	24
% Production Workers Unionized	B > 0	0.799 (1.940)	-0.243 (-0.210)	0.880 (1.906)	-0.790 (-1.645)	24

Stage-two regressions run estimated labor-demand elasticities on these regressors using weighted least squares. The specification is: (4) $(PED)_{it} = a + \sum_j b_j(\text{exogenous factors}_{ijt}) + \sum_i g_i(ID_i) + \sum_t d_t(TD_t) + e_{it}$.

Table 7

Stage-Two Regression Results
Explaining Nonproduction-Labor-Demand Elasticities
Estimated Parameters and (t-statistics)

Explanatory Variable	Hypothesized Effect on NP	No Controls	Industry Fixed Effects	Time Fixed Effects	Industry & Time Fixed Effects	# of Observations
Transportation Costs	B > 0	-1.817 (-1.713)	0.963 (0.428)	-1.598 (-1.425)	2.457 (0.844)	144
U.S. Share of World Value Added	B > 0	-0.069 (-0.626)	-0.491 (-2.358)	0.074 (0.600)	-0.275 (-0.525)	232
% Change in Domestic Prices	B > 0	-0.317 (-0.949)	-0.357 (-1.063)	-1.063 (-2.005)	-1.214 (-2.259)	264
% Change in (Prices-TFP)	B > 0	-0.248 (-0.917)	-0.282 (-0.922)	-0.838 (-2.053)	-0.900 (-2.147)	264
Outsourcing Broad	B > 0	2.485 (2.909)	4.328 (2.844)	2.386 (1.837)	5.770 (1.797)	24
Outsourcing Narrow	B > 0	5.676 (2.629)	8.481 (3.104)	5.336 (1.755)	9.323 (1.982)	24
Affiliate Share of U.S. MNC Assets	B > 0	0.687 (1.059)	1.962 (1.527)	0.727 (1.014)	2.944 (1.803)	78
Affiliate Share of U.S. MNC Empl	B > 0	0.651 (1.221)	0.884 (0.777)	0.459 (0.797)	0.717 (0.585)	80
Imports/ Shipments	B < 0	0.206 (0.836)	0.228 (0.767)	-0.116 (-0.353)	-0.558 (-1.127)	264
Net Exports/ Shipments	B > 0	0.436 (1.419)	0.075 (0.185)	0.930 (2.651)	0.959 (1.714)	264
% Change in TFP	B > 0	0.455 (0.545)	0.230 (0.271)	1.498 (1.350)	1.177 (1.022)	264
Computer Share of Total K Stock	B > 0	4.559 (1.670)	6.199 (1.489)	1.057 (0.234)	-1.034 (-0.134)	24
High-Tech Share of Total K Stock	B > 0	2.207 (1.519)	3.448 (1.628)	-0.699 (-0.289)	-1.305 (-0.275)	24

Stage-two regressions run estimated labor-demand elasticities on these regressors using weighted least squares.
The specification is: (4) (PED)it = a + Σjbj(exogenous factorsijt) + Σigi(IDi)+ Σtdt(TDt) + eit .