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THE LONG-RUN DEMAND FOR LABOR: ESTIMATES FROM CENSUS ESTABLISHMENT DATA

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Abstract

This paper estimates long-run demand functions for production workers, production worker hours, and nonproduction workers using micro data from U.S. establishment surveys. The paper focuses on estimation of the wage and output elasticities of labor demand using data on over 41,000 U.S. manufacturing plants in 1975 and more than 30,000 plants in 1981. Particular attention is focused on the problems of unobserved producer heterogeneity and measurement errors in output that can affect labor demand estimates based on establishment survey data. The empirical results reveal that OLS estimates of both the own-price elasticity and the output elasticity of labor demand are biased downward as a result of unobserved heterogeneity. Differencing the data as a solution to this problem greatly exaggerates measurement error in the output coefficients. The use of capital stocks as instrumental variables to correct for measurement error in output significantly alters output elasticities in the expected direction but has no systematic effect on own-price elasticities. All of these patterns are found in estimates that pool establishment data across industries and in industry-specific regressions for the vast majority of industries. Estimates of the output elasticity of labor demand indicate that there are slight increasing returns for production workers and production hours, with a pooled data estimate of .92. The estimate for nonproduction workers in .98. The variation in the output elasticities across industries is fairly small. Estimates of the own-price elasticity vary more substantially with the year, type of differencing used, and industry. They average -.50 for production hours, -.41 for production workers, and -.44 for nonproduction workers. The price elasticities vary widely across manufacturing industries: the interquartile range for the industry estimates is approximately .40.

Keywords: Labor Demand, Establishment Data, Measurement Error

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I. Introduction

In the last few years micro data sets derived from Census establishment surveys have proven valuable in analyzing several topics in labor demand.[1] However, as demonstrated in the recent synthesis of the literature by Dan Hamermesh (1993), knowledge of the magnitude of the basic labor demand parameters is still largely derived from studies using household surveys or aggregate producer data. The main goal of this paper is to provide a set of estimates of long-run demand functions for production workers, production worker hours, and nonproduction workers based on micro data from U.S. establishment surveys. The paper focuses on estimation of the wage and output elasticities of labor demand using data on over 41,000 U.S. manufacturing plants in 1975 and more than 30,000 plants in 1981.

While very valuable in modeling the structure of production, in general, and labor demand, in particular, firm or establishment survey data raise a set of unique empirical issues including survey coverage, data imputation, and biases arising from unobserved heterogeneity and measurement errors.[2] The second goal of this

[1] These include: the gross employment flows resulting from producer turnover(Dunne, Roberts, and Samuelson (1989a), and Davis and Haltiwanger (1990, 1992)), the duration of employment positions (Dunne and Roberts (1991)), the substitution of labor and nonlabor inputs (Griliches and Ringstad (1971), Sosin and Fairchild (1984), Mairesse and Dormont (1985), Kokkelenberg and Nguyen (1989) among others), and the effect of unions on the level of employment (Blanchflower, Milward, and Oswald (1991), Leonard (1991)). All of these studies utilize plant or firm surveys as their data source.

[2] Each of these problems has been discussed in the applied econometrics literature but they have not been treated systematically in many studies using establishment data. Griliches (1986) reviews all of these issues, as well as

paper is to identify the prevalence of several common econometric problems that arise when using establishment survey data and examine their implications for labor demand estimates.

In order to study these issues we apply a simple empirical model to plant-level data for a large number of industries and examine the results for consistency across industries and time. The empirical results reveal that OLS estimates of both the own-price elasticity and the output elasticity of labor demand are biased downward as a result of unobserved heterogeneity. Differencing the data as a solution to this problem greatly exaggerates measurement error in the output coefficients. The use of capital stocks as instrumental variables to correct for measurement error in output significantly alters output elasticities in the expected direction but has no systematic effect on own-price elasticities. All of these patterns are found in estimates that pool establishment data across industries and in industry-specific regressions for the vast majority of industries.

The final estimates of the output elasticity of labor demand indicate that there are slight increasing returns for production workers and production hours, with a pooled data estimate of .92. A pooled estimate of the output elasticity for nonproduction workers is .98. These estimates are much closer to constant returns to scale than are typically found in labor demand studies

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several measurement issues relevant to census establishment data.

using sectoral or aggregate time series data or in studies using microdata that ignore heterogeneity and output measurement error issues. Across three-digit industries the estimates do not vary widely as indicated by an interquartile range of approximately .14 for all three types of labor input.

The pooled data estimates of the own-price elasticity vary more substantially with the year or type of differencing used. They average -.50 for production hours, -.41 for production workers, and -.44 for nonproduction workers. The price elasticities vary widely across manufacturing industries: the interquartile range for the industry estimates is approximately .40. While the pooled data estimates are similar to those reported in other empirical studies, the amount of inter-industry variation indicates that wage changes will lead to very different employment adjustments among the manufacturing industries. The remainder of the paper is organized as follows. Section II outlines an empirical model of a plant's long-run demand for production and nonproduction workers. Section III describes the source of data and the construction of the variables used in the study. Section IV discusses the econometric specification. The empirical results are contained in Section V and Section VI concludes.

II. An Empirical Model of the Plant's Long-Run Demand for Labor

In the last decade estimation of flexible cost or production functions and systems of factor demands, has been a widely-used methodology, particularly for studies using aggregate or sectoral time-series data.[3] As detailed by Griliches (1986), movement to micro data results in an increase in the importance of omitted variables and measurement error problems. In order to explore the importance of these problems in the U.S. Census establishment data our empirical framework deviates from the recent trends in production modeling and relies on simple functional forms and single factor demand equations. Following Griliches and Ringstad (1971), Mairesse and Dormont (1985), Mairesse (1990), and Tybout and Westbrook (1992, forthcoming) we place greater emphasis on the likely sources of error arising in the micro-data and their implications for production estimates.

To develop the empirical model we assume that each plant has a production function in which production labor, nonproduction labor, capital, and electricity are combined into "value added" output that is separable from other material inputs.[4] The plant faces exogenous prices of each of these four inputs and, at the start of each year, chooses them to minimize the cost of producing a planned level of value added output. This cost minimization problem leads to a conditional labor demand function in which the plant's employment is expressed as a function of the prices of the

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[3] See Hamermesh (1986, 1993) for a analysis of the empirical models used in labor demand studies and Jorgenson (1988) for an overview of flexible-form production and cost models.

[4] We include electricity along with capital and labor in the "value-added" function because we have good data on plant-level electricity prices and can allow for plant-level substitution between electricity and labor inputs.

variable inputs and planned output. The demand for labor by plant i in year t is:

$$(1) \quad \ln L_{it} = \beta_0 + \beta_P \ln WP_{it} + \beta_N \ln WN_{it} + \beta_Q \ln Q^*_{it} + \beta_M DM_{it}$$

$$+ \sum_{j=1}^{5} \beta_j DAGE_{jit} + \beta_E \ln PE_{it} + \epsilon_{it}$$

The plant's demand for labor is expressed as a function of the log of the wages of production and nonproduction workers, WP and WN respectively, the log of planned value added output Q^*, a dummy variable for plant ownership DM, a set of dummy variables for plant age categories $DAGE_1 ... DAGE_5$, and the price of electricity PE faced by the plant. As is generally the case with establishment data, we do not have information on plant-level capital service prices. The ownership dummy is included as a proxy for the price of capital, allowing it to differ for plants owned by single and multi-plant firms.[5] The age dummies are included as proxies for possible differences in the vintage of the plant's capital stock, for differences in plant efficiency, or for differences in the tenure and experience of the plant's workforce.[6]

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[5] In the econometric section we will apply an estimator that can control for omitted variables that are common to all plants owned by the same firm. To the extent that cross-section variation in the capital service price results from firm-level differences in the opportunity cost of funds, this estimator will control for the omitted capital price.

[6] The model of plant heterogeneity and market selection developed by Jovanovic (1982) predicts that more efficient plants will tend to survive longer. In the cross-section plant age thus provides a useful control for unobserved efficiency differences as well as capital vintage effects.

The labor demand equation is estimated separately for three different types of labor input: the number of production workers, total production worker hours, and the number of nonproduction workers. Equation (1) will first be estimated by pooling over plants in all industries, and including dummy variables to control for industry fixed effects. We then estimate equation (1) separately for each three-digit SIC manufacturing industry in order to study the variability in wage and output elasticities across industries.

The appropriate estimator for equation (1) depends upon the sources of the random shocks O_{it}. In the fifth section of this paper we discuss the likely sources of error in the establishment data and the estimators that are appropriate under different conditions.

III. Establishment Data

A. Description of the Data Samples: The data used in this paper are for the individual establishments in the U.S. Annual Survey of Manufacturing (ASM) for the years 1975 and 1981. The ASM is a yearly survey conducted by the Census Bureau which covered approximately 71,000 plants in 1975 and 55,000 plants in 1981. The survey does include small manufacturing establishments and provides good cross-sectional variation in plant employment levels. In addition, plants in the two cross-sections have been matched over time so that changes in plant employment can be examined. There are two reasons for using the 1975 and 1981 samples. First, in these two years the ASM questionnaire asked for the initial year of plant operation and this allows us to control for plant age when estimating labor demand equations. Second, we were best able to identify and eliminate plant's with imputed data in these two years.[7]

The labor demand equations are estimated separately for three-digit manufacturing industries and the dispersion in coefficients across industries is examined below. Some three-digit industries have relatively few plants in the ASM and estimates for these industries are likely to be noisy because of the small sample sizes. To eliminate coefficient variation due to industries with few plants we limit our data set to those plants operating in three-digit industries with at least 100 plants. The final cross-sectional data sets we use contain 41,576 plants in 1975 and 30,176 plants in 1981. These plants cover 105 three-digit industries in 1975 and 90 industries in 1981 and account for 58.5 and 48.2 percent of total manufacturing employment in 1975 and 1981, respectively.

[7] In its processing of the ASM, the Census Bureau imputes the values of several employment and output variables for plants that fail to answer the questionnaire completely, or fail to return it. These imputed values are often impossible to identify in the data sets. The starting year of operation is one variable that is never imputed and so, by eliminating plants that do not report this information, we are able to eliminate virtually all plants for whom the key employment, payroll, or output variables we use are imputed. The overall response rate to this question was 71.8 percent in 1975 and 67.2 percent in 1981. Additionally, we also remove from the sample a small set of plants that are extreme outliers.

In addition to these two annual cross-section data sets, we utilize three subsets of the data to control for unobserved plant and firm-level heterogeneity. The first subset contains only those plants that appear in both 1975 and 1981 and is used to examine the change in plant employment as one way to control for unobserved plant effects. This eliminates all plants that opened after 1975, failed between 1975 and 1981, or continued in operation but were rotated out of the ASM survey group between the two years. Because of the way in which the Census Bureau selects the ASM survey group, this rotation will tend to eliminate the smaller plants in the sample.[8] There are a total of 16,893 plants that we observe in operation in both years and this group is more heavily skewed toward large plants than either of the separate cross-sectional ASM surveys. This last point is illustrated in Table 1 which reports the mean and standard deviation of the log of production hours, production workers, and nonproduction workers for each of the data sets. The group of plants used in the time-difference regressions are summarized in the middle panel of the table, and it can be seen that they are larger on average and with less size dispersion than the cross-section samples summarized in the top panel.[9]

[8] This occurs because smaller plants in an ASM panel are intentionally replaced when a new panel is selected in order to reduce the reporting burden on them. The two years we use are drawn from two different ASM panels, one covering 1974-1979 and the other covering 1980-1985.

[9] Issues of selection bias arising from the plant's decision to exit become important when using time series data on individual producers. Olley and Pakes (1992) develop a theoretical and empirical model that recognizes that exit decisions may be based upon unobserved productivity differences across producers.

The final two subsets of data are used to control for unobserved firm effects in the labor demand equations by examining the within-firm variation in plant employment. In each of the two yearly cross-sections we identify all firms that own two or more plants in a year. The subsets, one for 1975 and one for 1981, include the plants owned by the multi-plant firms in that year. Overall, the 1975 firm data set contains 32,492 plants owned by 4162 different firms and the 1981 data set contains 19,269 plants owned by 2800 firms. There is one important difference in the selection criteria used in the 1975 and 1981 ASM's. In both years plants were selected into the sample in proportion to their size. In 1975 for each plant that was selected for inclusion the Census Bureau also surveyed all other manufacturing plants owned by the same firm. As a result there is complete firm coverage for each plant in the sample. In 1981 complete firm coverage was dropped. The main implication of this change is that the 1981 subset contains fewer observations because there are fewer firms with two or more plants covered by the ASM. Despite the drop in sample size, these data sets have a mean size and level of dispersion that is very similar to the complete cross-section data sets, as can be seen from the last panel in Table 1.

They find that limiting their analysis to a balanced panel of surviving plants results in selection bias in production function coefficients. An important factor that mitigates selection bias problems in the time-differenced data set in this study is that much of the sample attrition does not result from an endogenous exit decision by the plants, but rather results from a Census selection rule that is uncorrelated with the error term in the individual plant's labor demand equation.

B. Description of the Variables: The variables of primary importance to this study are the level of employment and the plant's expenditure on labor for both production and nonproduction workers. The labor input for production workers is defined using both the number of hours worked and the number of employees. The corresponding prices of production labor are defined as the average hourly wage and the average annual salary of production workers in the plant. Separate demand functions will be estimated for production worker employment and hours. For nonproduction workers, only annual employment levels and annual salaries are collected in the ASM so the demand for nonproduction workers will always be estimated as the demand for workers, not hours.[10]

Output is defined as the plant's value-added and measured as the total value of shipments plus changes in inventories minus expenditure on materials and energy (other than electricity). Price deflators for the value of shipments and material expenditures are only available at the four-digit SIC level. Rather than deflating shipments and material expenditures to

[10] The measured wage for production and nonproduction workers does not include the nonwage costs associated with labor for two reasons. First, the census only collects data on the total nonwage costs in the plant and does not disaggregate these costs for production and nonproduction workers. Any attempt to construct separate nonwage costs for production and nonproduction workers in the plant is a guess. Second, nonwage costs are a poorly reported variable in the census data. As a result many of the plants have this variable imputed and we felt that it was inappropriate to include it in the measurement of labor cost. Hamermesh (1983) finds that the use of broader measures of labor cost results in an increase in the (absolute value) of the estimated wage elasticities. Using micro data on Colombian manufacturing plants, Roberts and Skoufias (1992) find that inclusion of nonwage payments generally lowers estimated wage elasticies although this pattern does not characterize all industries.

construct real value added we include four-digit industry dummy variables in all regressions. Since the output variable is measured in logs this is equivalent to using the four-digit industry price deflators. The ownership type of the plant can be measured within each of the separate cross-sections and is a dummy variable equal to one for plants owned by multi-plant firms.[11] The capital stocks of equipment and structures are used as instrumental variables in the estimating model. Both variables are measured as the book value of the plant's capital in that category at the beginning of the year.

IV. Econometric Specification

A recurring theme in studies using U.S. manufacturing establishment-level data is the enormous variation in plant size and its persistence over time, even within narrowly-defined industries. While some of these differences can be attributed to factors that are frequently measured in establishment surveys, such as input prices, ownership structure, and plant age, and are included as observable characteristics in equation (1), there is also a substantial role for factors that these surveys do not record. This unobserved heterogeneity can arise at the plant

[11] Virtually all studies using the U.S. Census establishment data have found that it is important to distinguish plants owned by multi-plant firms from those owned by single-plant firms. See Dunne, Roberts, and Samuelson (1989b) and Davis and Haltiwanger (1992) for examples. In this case, the employment level in single-unit plants will generally include managerial or central office staff that may be located in a separate facility for multi-unit plants.

level, as a result of differences in organization, vintage of capital equipment, extent of unionization, or quality of output produced. It can also arise at the firm level because of differences in capital prices, firm-level inputs such as R and D, and the amount or quality of management inputs.

Many of these factors differ across plants and firms and, if recognized by the plant managers when making production decisions, can lead to permanent observable differences in plant output, employment, and wages. Failure to recognize this can lead to a simultaneity bias in the estimated labor demand equations using establishment data.[12] Since many of these factors change slowly over time, if at all, it is reasonable to treat them as time-invariant, plant- or firm-specific effects when specifying the econometric model. Plant-specific, or firm-specific, effects can also arise from differences in the quality of labor across plants. Because we measure only the number of workers or hours and cannot control for the occupation, education, or skill mix of the workers we will systematically underestimate the quantity of labor in plants with high-quality workers. Similarly, because we measure the wage rate as the plant's expenditure on labor divided by the quantity of labor, we will systematically overestimate the wage for plant's with high-quality workers. These two measurement errors

[12] This point has been well-discussed in the literature. Tybout and Westbrook (1992) provide a useful summary of the effect of unobserved heterogeneity on scale estimates using both production function and cost function or factor demand models.

will result in a negative bias in the own-wage elasticities. In this paper we will treat these labor quality differences as time-invariant plant or firm effects.[13]

The second source of error in the labor demand equations arises from year-to-year fluctuations in establishment output as a result of unobserved demand shocks, equipment breakdowns, strikes, input shortages, and reporting errors. If the plant's employment does not respond to these random occurrences the observed output of the plant may be a poor measure of the permanent or long-run output level on which the plant's employment decisions are based. This source of variation is identical to an errors-in-variables problem in output. Denote the plant's <u>planned</u> or permanent output Q^*_{it}. Assume $<_{it}$ is a zero mean, constant variance measurement error that is uncorrelated with the log of the plant's planned output, $\ln Q^*_{it}$. The observed output of the plant, that is used as the regressor in equation (1), can be written as $\ln Q_{it} = \ln Q^*_{it} + <_{it}$. In general, this problem will bias the output coefficient toward zero in the labor demand equation, and the solution is to construct an instrumental variable that is correlated with the plant's permanent output but uncorrelated with the random fluctuations to output.

[13] If plants respond to demand fluctuations by altering the mix of skill groups or occupations within the plant, then average labor quality in the plant is also likely to vary over time. There is no information in census establishment data that can be used to control for variation in labor quality over time. Separating labor into production and nonproduction categories and allowing for time-invariant plant or firm effects are the best controls for quality variation that we could implement with this data.

The final source of error is pure random shocks to the labor demand equation that vary across plants and over time. Recognizing these three sources of random variation implies that the error term in the labor demand equation can be written as:

$$(4) \qquad O_{it} = \mu_i - \$_Q <_{it} + g_{it}$$

Variation arising from time-invariant plant heterogeneity is denoted by μ_i, variation arising from measurement error in output results in the term $- \$_Q <_{it}$, where $\$_Q$ is the coefficient on output in the demand equation, and g_{it} represents idiosyncratic shocks to labor demand. Each of the three error components is assumed to be a zero mean, constant variance, random variable that is uncorrelated with the other error components. The error components arising from unobserved heterogeneity and measurement error are allowed to be correlated with the regressors in the estimating equations.

Given these assumptions on the stochastic structure of the labor demand equations, ordinary least squares (OLS) estimates of the parameters will be biased. As emphasized by Griliches (1986), Griliches and Hausman (1986), Mairesse and Dormont (1985), and Mairesse (1990), the magnitude of the bias will vary with the type of data used to estimate the equation. Estimates from cross-sectional data or panel data in which the majority of variation is in the cross-sectional dimension are more likely to suffer bias from the presence of μ_i. Time series data, or data expressed as changes over time, are more likely to be affected by measurement errors.

It is also possible to identify the likely direction of the bias in the own-price and output elasticities. In the case of unobserved efficiency differences, high values of μ_i denote inefficient plants so μ_i will be negatively correlated with output and wages resulting in a negative bias in both the output and own-price elasticities.[14] If the unobserved plant heterogeneity arises from variation in labor quality then OLS estimates of the wage and output elasticities will be also be subject to a negative bias. Overall, if there is unobserved plant-level heterogeneity, OLS will tend to underestimate the output response and overestimate the own-price response of plant-level employment.[15]

The correlation between $<_{it}$ and $\ln Q_{it}$ resulting from measurement error biases OLS output elasticities toward zero (Griliches, 1986). Output measurement error can also bias the estimates of own-price elasticities. Griliches (1986, p. 1479) shows that the bias in the

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[14] Many theoretical models predict an inverse relationship between a producer's efficiency and output level. See Jovanovic (1982) for a competitive model that produces this correlation. The inverse relationship between plant size and wages is a very robust empirical regularity, see Brown and Medoff (1989).

[15] If μ_i represents differences in capital service prices then the direction of bias in the wage and output coefficients will depend upon whether capital and labor are substitutes or complements. If they are substitutes (complements), plants with higher capital prices will use more (less) labor. Capital service prices will tend to be negatively correlated with plant output and wages and this will result in a negative (positive) bias in the output and own-price elasticities. If capital is a complement with skilled labor but a substitute for unskilled labor, then the elasticities in the two labor demand equations would be biased in opposite directions.

coefficient for the error-ridden variable is transmitted to other coefficients with the opposite sign, if the variable not subject to measurement error is positively correlated with the observed, error-ridden variable. Because wages and output are positively correlated in our data, the own-price elasticities will be biased toward zero with the magnitude of the bias increasing as the correlation between output and wages rises. Overall, output measurement errors will result in OLS coefficients that underestimate the output and wage responsiveness of employment.

The basic econometric problem is to correct for the possible correlation between $\ln Q_{it}$ and the errors $<_{it}$ and μ_i. To remove the plant-specific error μ_i we utilize two forms of data differencing. The first is the difference between the two years 1981 and 1975, which we refer to as the "long time difference". In this case the dependent variable is the change in the plant's employment or hours between the two years and the regressors are the changes in the logarithms of the average wage of production and nonproduction workers, the price of electricity, and output. The second form of differencing relies on the multiple observations for plants owned by the same firm and expresses each plant's data as deviations from firm means. This type of differencing removes any plant characteristics that are common to all plants owned by the firm. This could include, for example, capital prices or firm-level administrative inputs. While this type of differencing removes all firm-level factors it preserves the within-firm variation across plants. If the unobserved plant heterogeneity arises because of factors that are common to all plants owned by the firm, then this form of differencing removes the source of output bias. We refer to this as the "firm-difference" estimator.

While both difference estimators correct simultaneity problems arising from permanent unobserved plant or firm-level factors, Griliches (1986) and Griliches and Hausman (1986) demonstrate they can exaggerate the bias due to measurement error by reducing the amount of systematic variation in the explanatory variables and thus reducing the ratio of signal to noise in the data. They also show that the bias will generally diminish as longer time differences are used. In this case the use of time differences, even when they are taken over six year periods, is likely to destroy much of the systematic or permanent differences in plant size and, thus, it is likely that the downward bias in the output elasticities resulting from output measurement error will be more severe than when the data are expressed in levels.

Expressing the data as differences from firm means is also likely to exaggerate the bias due to measurement error but it should not be as severe. Firm differencing retains much more of the cross-sectional variation in the plant data and thus does not have as severe an impact on the systematic variation in the data as time differencing.[16]

In order to deal with measurement error problems in the differenced data we use the instrumental variables (IV) estimator. We require an instrument that is correlated with the planned output of the plant but uncorrelated with the random fluctuations to output and the plant's beginning-of-year capital stock meets these requirements. In the case of the time-differenced data, the instruments are a fourth-order polynomial in the plants' equipment capital stock and structures capital stock for both 1975 and 1981. For the firm-differenced data, the fourth-order polynomial in the two capital stocks for the same year is used as an instrument.[17]

In summary, the labor demand equation (1) is estimated separately for production hours, production workers, and nonproduction workers. Three estimation methods are used, each of which treats unobserved plant heterogeneity and measurement error in output differently. We first estimate the labor demand equations with ordinary least squares using the cross-sectional data and ignoring the potential biases from unobserved heterogeneity and measurement error. The OLS estimates will be denoted $\hat{\beta}$. Second, long time differences (denoted as $\hat{\beta}_{TD}$) and firm

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[16] The wage elasticities are also likely to be biased toward zero but the magnitude of the bias now depends on the correlation between the difference in output (either over time or within firms) and the difference in wages and it is not clear how substantial this will be.

[17] In regressions that pool plants across industries, dummy variables for the four-digit SIC industry are also included as instruments.

differences ($\hat{\beta}_{FD}$) are used to control for unobserved heterogeneity, but at the cost of larger measurement error bias. Finally, to correct for both problems, instrumental variables estimators are constructed for the time-difference data ($\tilde{\beta}_{TD}$) and firm-difference data ($\tilde{\beta}_{FD}$).

VI. Empirical Estimates of the Long-Run Demand for Labor

In this section we focus primarily on the estimates of the output and own-wage elasticities. A complete set of parameter estimates for equation (1) are reported in the appendix tables A1-A3. Separate demand equations were also estimated for each three-digit industry but only the output and wage elasticities are discussed in this paper.[18]

A. Long-Run Output Elasticities

The output elasticity estimates from the pooled regressions are reported in Table 2. The first column reports OLS estimates from the cross-sections in 1975 and 1981. The second column reports estimates based on the difference in the plant's labor input between 1975 and 1981. The third column reports estimates using the within-firm variation in each of the two cross sections. The

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[18] Separate demand equations were not estimated at the four-digit level because of the large number of industries and the relatively small sample sizes that would result in many cases. Separate results at the three-digit industry level are more than sufficient to identify whether the effects of unobserved heterogeneity and measurement errors are common across the manufacturing sector. A listing of the coefficient estimates at the three-digit level is available from the authors.

fourth and fifth columns report IV estimates using the time-differenced and firm-differenced data, respectively.

Production Hours: In order to simplify the presentation of results and illustrate the problems created by heterogeneity and measurement errors we focus first, and in some detail, on the estimates of the output elasticities for production hours, reported in the top part of Table 1. In later subsections we discuss how the estimates for production and nonproduction workers differ from these and then turn to discussion of the own-wage elasticities.

The OLS estimates of the output elasticity for production hours are .804 and .775 in the two cross-sections. Given the large sample sizes, 41,576 plants in 1975 and 30,176 plants in 1981, it is not surprising that the standard errors on the estimates are very small. These estimates are very similar to other estimates of the labor-output elasticity reported in the literature and indicate increasing returns to scale in production. Based on a survey of labor demand studies that control for factor price variation, Hamermesh (1993, p. 294) reports a mean estimate of the long-run employment-output elasticity of .83.[19] While the capital/labor ratio increases with plant size, and thus the output elasticity for

[19] From the results of 101 studies using a wide variety of data and empirical models Hamermesh (1993, Table 7.9) finds that the mean estimate of returns to scale from labor demand equations is .792. When limited to the few studies using micro data he finds a mean estimate of .62. Hamermesh notes that errors in measuring output at the plant level may impart a negative bias to estimates based on micro data.

labor could be less than one, these magnitudes appear to be quite low and suggest that a downward bias from unobserved heterogeneity and/or measurement error in output may be present.

If the bias from unobserved heterogeneity is important then differencing the data should result in coefficients that are closer to one. Instead, the empirical results reported in the second and third columns of Table 1 indicate that differencing always results in a <u>decline</u> in the output coefficients. In the case of time differencing the output elasticity falls to .366, and for firm differencing the coefficient falls to either .713 or .775 depending on the year. The likely explanation is that differencing the data increases the bias from measurement error in output.[20] In particular, the decline in coefficients depends on the method of differencing and is much more extreme for time differencing than firm differencing. This is consistent with the fact that firm differencing preserves much more of the original output variation in the data and thus results in a smaller increase in the noise-to-signal ratio and less downward bias than time differencing.

IV estimates to correct for the output measurement error are reported in columns 4 and 5 of Table 2. As expected, instrumenting with the plant's capital stock results in an increase in the output

[20] This problem is common in estimates of production models using micro data. Griliches and Mairesse (1984), Mairesse and Dormont (1985), Griliches and Hausman (1986), Tybout and Westbrook (1992a, forthcoming), and Roberts and Skoufias (1992) all develop production models with plant-specific heterogeneity and use first-difference or within estimators to correct for it. All report substantial declines in coefficients when they utilize difference estimators and point to increased measurement error bias as the source of the decline.

elasticities, with the final estimates being substantially closer to one than any of the earlier estimates.[21] In the case of time differences, the output elasticity is .934 while with firm differences the estimates are .923 and .916 in the two years.[22] These estimates are not very sensitive to the time period or method of differencing, which suggests that the two procedures work well to correct the biases from heterogeneity and measurement error. The magnitude of the estimates suggest that in the long run production worker hours increase less than proportionately with output, but the estimated values of .916 to .934 are substantially closer to one than the majority of estimates in the literature.[23]

While the estimates in Table 2 clearly illustrate the potential biases in estimating long-run labor demand functions using establishment data, they do not allow industry variation in the output elasticity or the magnitude of the biases. To assess whether the patterns reported in Table 1 are common across the manufacturing industries we estimate separate labor demand

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[21] As expected, there is an increase in the standard errors of the coefficients when the IV estimators are used. The standard error for $\tilde{\beta}_{TD}$ is approximately four times larger than for $\hat{\beta}_{TD}$. Similarly the standard errors for $\tilde{\beta}_{FD}$ are double the values for $\hat{\beta}_{FD}$.

[22] The IV/time difference estimate of .934 does not result because only larger plants, that are more likely to produce under constant returns to scale, remain in the time-differenced data set. Cross-section estimates of the output elasticity, using only the sample of surviving plants, are .765 and .727 in the two years. It is the instrumenting to remove output measurement errors that is responsible for the increase in the output elasticity.

[23] When they use capital as an instrument for output, Griliches and Hausman (1986) get output elasticity estimates very close to one in a labor demand equation.

functions for each three-digit industry. Overall, there are sufficient plant-level observations to analyze 105 three-digit industries in 1975 and 90 industries in 1981.

Summary results for the output elasticity from the separate industry regressions are presented in Table 3. The first two columns report the median and interquartile range (IQR) of the output elasticities from the industry-level OLS regressions. The third and fourth columns report the proportion of industries that have an <u>increase</u> in the estimated elasticity when differencing is used. The fifth and sixth columns examine the effect of instrumenting output by reporting the proportion of industries in which the IV estimator is <u>larger</u> than the difference estimator. Finally, the last two columns quantify the effect of these corrections on the distribution of industry-level output elasticities by reporting the median and IQR for the IV/firm difference estimates.

Focusing on the OLS estimates, the median values of the output elasticity for production hours are .822 and .803 which are very similar to the pooled results in Table 2. The interquartile range equals .111 and .140 in the two years, indicating a fairly narrow range of estimates across industries and that most industries are characterized by long-run increasing returns to scale. Regardless of the magnitude of the industry's output coefficient, the direction of change in the coefficient as a result of differencing the data or instrumenting output is very similar to the patterns in

Table 2. With time differencing only one three-digit industry has an increase in the output elasticity, and with firm differencing an increase is observed in only 20.0 to 29.5 percent of the industries. Differencing, particularly over time, reduces estimated output elasticities in most industries. Similarly, the use of instrumental variables results in an increase in the output elasticity in 86.7 to 93.3 percent of the industries, depending on the time period and differencing used. Overall, the patterns observed in Table 2 hold widely across the manufacturing industries.

The final two columns of Table 3 report summary statistics of the output elasticities across industries for the IV/firm difference estimator. The median estimates are .918 and .930 in the two years, with an IQR of .120 and .148. Compared with the distribution of OLS estimates in columns 1 and 2, this distribution is shifted toward one, with an absolute increase in the median of approximately .1, and has a slightly larger dispersion.[24]

Production Workers: The estimates of output elasticities for production workers reported in Table 2 are virtually identical to the estimates for production hours. OLS estimates are .798 and .766. The estimate is substantially lower for time differences

[24] Given the higher standard errors associated with IV estimators, it is not surprising to see a larger IQR on the distribution of IV estimates. The difference in the IQR between the OLS and IV estimates, however, appears quite small.

(.358) and slightly lower for firm differences (.771 and .705). IV estimates vary from .904 to .929 depending on the year and method of differencing. As with the production hours, the OLS estimates appear to be downward biased due to unobserved heterogeneity and output measurement error. Finally, the distribution of estimates across industries, which is summarized in Table 3, is virtually identical to that reported for production hours.

The strong similarities between the estimates for production hours and production workers suggest that, across plants, there is little systematic variation in the annual hours per worker. While the hours-worker distinction has played an important role in explaining short-run labor demands, the micro estimates here suggest that the distinction is unimportant for studying the effect of long-term differences in manufacturing output on employment. Alternatively, the fact that the responses of hours and workers to output differences are so similar suggests that the estimates do summarize the long-run employment elasticities, rather than reflecting cyclical variation in the output-employment relationship.

Nonproduction Workers: The pooled estimates for nonproduction workers reported in Table 2 follow an identical pattern to that for production workers. The only difference is that the final IV estimates, using both time and firm differencing, are slightly closer to one. The final IV estimates are .953 and .983 for firm differencing and .997 for time differencing. The latter estimate is not significantly different than one, and implies that the employment of nonproduction workers varies proportionately to output in the long run. Again, the same pattern is evidenced by the separate industry estimates. The only differences from the distribution for production workers is a slightly higher degree of dispersion across industries, the IQR is .145 and .165 in the two years, and firm differencing has very little effect on the OLS estimates. In the latter case, 46.7 and 47.8 percent of the industries have firm difference estimates that are greater than the OLS estimates, and this is consistent with no systematic bias in the coefficients.[25]

Overall, there are several robust findings concerning the output elasticities. First, the OLS estimates for all three definitions of labor are in the .77 to .80 range and appear to be downward biased due to unobserved heterogeneity and output measurement error. Second, differencing the data to remove the heterogeneity exaggerates the measurement error in output. The

[25] There are several possible explanations for the fact that the OLS and firm differences are so similar. One is that unobserved heterogeneity does not play any role in the demand for nonproduction labor. A second is that it does play a role, but that it is plant, and not firm, specific. A third is that it is present but the bias that is removed by firm differencing is just counterbalanced by the increase in measurement error bias. The second explanation is inconsistent with the fact that IV estimates using time and firm differences are very similar. The latter should still be biased downward if the firm differences are ineffective in controlling for the unobserved heterogeneity. The third explanation also appears unreasonable because it requires that the two biases offset each other across almost all industries.

problem is particularly important for the long-time differences. Time differencing the data to remove the plant level heterogeneity reduces the estimates considerably, to the range of .29 to .37, while firm differencing reduces them slightly, to the range of .71 to .79. Third, differencing the data and using the plant's capital stock as an instrument for output results in estimates of the output elasticities that are reasonable and not very sensitive to the time period or method of differencing. The estimates fall in the range of .90 to .93 for production workers and production hours and .95 to 1.0 for nonproduction workers.

B. Long-Run Wage Elasticities Production Hours: Estimates of the own-wage elasticity based on pooling plants across all industries are reported in Table 4. The OLS estimates for production worker hours are -.621 in 1975 and -.609 in 1981. Not surprisingly, given the sample sizes, the estimates are highly significant.

As described above, these elasticities may be biased away from zero as a result of unobserved heterogeneity. Consistent with this, both methods of differencing result in less elastic wage coefficients. The long-difference estimate is -.499 and the firm-difference estimates for 1975 and 1981 are -.508 and -.485, respectively. Interestingly, in this case, the method of differencing has little effect on the final estimates. Since time differencing removes both plant and firm effects while firm differencing only removes the latter, the similarity of the estimates suggests that the important source of interplant heterogeneity arises at the firm level. This is consistent with firm-level quality differences in labor input.

It is possible that estimates based on differenced data may still be too large as a result of output measurement error. However, when we use the IV estimator there are no large or systematic changes in the wage elasticities. For both the long time differences and the firm differences in 1975, the estimates fall slightly, to -.486 and -.461 respectively. In contrast, the firm difference estimate for 1981 rises to -.567. Overall, the final IV estimates of the own-price elasticity are noisier than the OLS estimates, varying more with the year or estimation method.

These patterns are also reinforced by examining the estimates for the three-digit industries summarized in Table 5. The first column indicates that the median OLS estimates across industries for 1975 and 1981 are virtually identical to the OLS estimates on the pooled data summarized in Table 4. The IQR reported in column 2 indicates that there is substantial dispersion in the estimates across industries. It equals .362 and .349 in 1975 and 1981, respectively. This indicates a larger degree of inter-industry heterogeneity in the wage elasticities than was found in the output elasticities.

As shown in the third and fourth column of Table 5, differencing the data tends to result in <u>less</u> elastic wage coefficients. The magnitude of the differenced estimate is greater (in absolute value) than the OLS estimate in 21.9 to 40.0 percent of the industries. This shift toward less elastic demands was also seen in the pooled estimates in Table 4. When instruments are applied to the differenced data the direction of change in the coefficients is not systematic. The IV estimates are farther from zero for between 50.0 and 56.2 percent of the industries, depending on the year and differencing method. This is the same pattern that would be expected if there was no measurement error bias in the differenced coefficients.

The overall conclusion from examining the own-wage elasticity for production workers is that heterogeneity bias appears to be present, and it results in estimates that are too elastic, but that measurement error in output seems to have little additional effect on the estimates.

Production Workers: The patterns in the production worker wage elasticities across different estimators are very similar to the corresponding patterns for production hours. Differencing tends to make the estimates more inelastic and instrumenting has no systematic effect. If there is any systematic difference in the wage responsiveness of the two categories of production labor it is that the demand for production hours is more elastic than the demand for workers when the time difference estimators are used.

Nonproduction Workers: The own-price elasticities for nonproduction workers are reported in the bottom panel of Table 4. The OLS estimates are -.481 and -.546 in the two cross-sections. Unlike what we observe for production workers, differencing the data has little systematic effect. This suggests that labor quality differentials may not be very important for nonproduction workers. This is supported by the absence of a strong pattern in the change in the industry-level wage elasticities. In Table 5, approximately 40 percent of the industries have difference estimates that are more elastic than the OLS estimates while the remaining 60 percent are less elastic. Finally instrumental variable estimators tend to be less elastic than the difference estimates, but the change in the magnitude of the wage elasticities is small. The final IV estimates on the pooled data vary from -.378 to -.488 depending on the method used for differencing.

Overall, five broad conclusions can be drawn regarding the estimation of own-price elasticities from establishment data. First, there is strong evidence of plant-level employment adjustment for both production and nonproduction workers in response to wage differences. For production hours the median value of the wage elasticity across industries, correcting for heterogeneity and measurement error biases, is -.54 on average across years. The same values for production and nonproduction workers are -.42 and -.43, respectively. This is very close to Hamermesh's (1993, p. 103) finding that the mean estimate of the demand elasticity across a wide range of studies is -.45. Second, the own-wage elasticity varies significantly across industries. In particular, the dispersion in estimates is much larger than the dispersion of the estimated output elasticities. At the three-digit industry level the interquartile range for the wage elasticity is approximately .4 for production workers and hours and .3 for nonproduction workers. The range of estimates suggests that the impact of wage changes on employment will vary widely across industries. Third, OLS estimates of the long-run wage elasticity for production workers and production hours overestimate the wage response by approximately 15-20 percent. This bias is consistent with a failure of the OLS estimator to control for time-invariant quality differences in production workers (or other sources of efficiency differences) among plants and firms. Fourth, differencing the data to control for unobserved heterogeneity does not appear to exaggerate biases due to measurement error in output. Given the second-order nature of this bias this is not surprising. Finally, there does not appear to be any substantial, systematic bias in the wage elasticities for nonproduction workers. This could indicate that unobserved labor quality differential among plants is small.

C. Other Determinants of Long-Run Labor Demand

In addition to own wages and output the labor demand equations also control for the wage of the other type of labor, plant age, ownership status, and electricity prices. In this section we briefly summarize the findings for the these variables in the regressions that pool plants across industries. The complete set of parameter estimates is reported in Appendix tables A1-A3. The estimated cross-wage elasticities do not appear to be very large nor to be very robust. The OLS estimates are negative in 5 of the 6 regressions implying that production workers (hours) and nonproduction workers are complements. However, all but one of the IV estimates on the differenced data are positive implying that the two types of labor are substitutes. In virtually all cases the cross-wage elasticities are small, less than .07 in absolute value, and are often not significantly different than zero. Probably the strongest conclusion that can be drawn from these results is that there is no evidence of large cross-price effects in the plant data.

In contrast, there is evidence of strong age effects in the demand for all three types of labor. The age coefficients are large, increase monotonically as you move toward older age groups, and are similar across estimation methods. For example, the OLS estimates in the 1981 cross-section indicate that, holding output fixed, plants that opened prior to 1950 use 24 percent more production hours than plants that opened after 1975. The age coefficients indicate that older plants have substantially lower levels of labor productivity than younger plants and that the decline is monotonic as plant age increases.[26] The decline also occurs at roughly the same rate for both production and nonproduction workers.

The coefficient on the plant ownership type indicates that plants owned by multiplant firms have more labor input, a common finding in the U.S. census data. The final coefficient summarizes the substitution between labor and electricity. The negative coefficient for the price of electricity in the production worker and hours equations indicates that electricity and production labor are complements. The positive cross-price effect for nonproduction workers indicates that they are a substitute for electricity. The signs of the cross-elasticities are not sensitive to the year or estimation method. While the magnitude of the elasticities vary with the estimation method and year, they are generally small. The finding that electricity and production labor are complements runs counter to the usual empirical finding that labor and broad-based energy inputs are p-substitutes (Hamermesh 1993, p.105).

VII. Conclusion

[26] This could reflect a different vintage of capital equipment in plants of different ages, with newer equipment requiring less labor to operate. An alternative explanation is that, since older plants tend to produce more output, the age coefficients pick up a nonlinearity in the employment-output relationship, and their presence may be responsible for the low output coefficient. To examine this we reestimated the three labor demands deleting all the age coefficients and there was virtually no change in the estimated output elasticities. The OLS elasticities never increased by more than .025 for all three labor type in both sample years, suggesting that the age and output effects are distinct.

In his review of the labor demand literature, Hamermesh (1993) concludes that demand estimates for heterogeneous groups of labor, based on microdata for producers, are almost nonexistent. In this paper we have utilized two large, matched, cross-section data sets of U.S. manufacturing establishments to estimate long-run labor demand curves. We focus on the type of measurement, specification, and econometric problems that are frequently encountered in establishment data sets and identify several problems that occur with high frequency.

Unobserved plant or firm-level factors are important and, when ignored, introduce systematic biases in labor demand coefficients. They introduce a negative bias in OLS estimates of the wage and output elasticities so that OLS overestimates the long-run response of labor to wage changes and underestimates the output response. Differencing the data to remove unobserved heterogeneity appears to remove the bias from wage elasticities but greatly exaggerates measurement error biases in the output elasticities. Capital stocks appear to be reasonable instrumental variables for output and their use removes, or at least reduces, measurement error biases in the output elasticities, at the cost of reducing the precision of the estimated wage elasticities.

The final estimates of the output elasticity of labor demand are much closer to constant returns to scale than are typically found in labor demand studies using either aggregated time series data or micro data but ignoring measurement error problems. The results indicate slight increasing returns for production workers and production hours, with a pooled data estimate of .92. A pooled estimate of the output elasticity for nonproduction workers is .98. The across-industry variation at the three-digit industry level is modest with an interquartile range of approximately .14 for all three type of labor input. The pooled data estimates of the own-price elasticity average -.50 for production hours, -.41 for production workers, and -.44 for nonproduction workers but vary substantially across industries as indicated by an interquartile range of approximately .40.

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Table 2

Output Elasticities of Labor Demand
(standard errors in parentheses)

	OLS $\hat{\$}$	Time Difference $\hat{\$}_{TD}$	Firm Difference $\hat{\$}_{FD}$	IV/Time Difference $\tilde{\$}_{TD}$	IV/Firm Difference $\tilde{\$}_{FD}$
Production Hours					
1975	.804		.775		.923
	(.002)		(.003)		(.006)
1981	.775	.366	.713	.934	.916
	(.003)	(.005)	(.004)	(.019)	(.008)
Production Workers					
1975	.798		.771		.917
	(.002)		(.003)		(.006)
1981	.766	.358	.705	.929	.904
	(.003)	(.004)	(.004)	(.033)	(.008)
Nonproduction Workers					
1975	.800		.778		.953
	(.003)		(.004)		(.007)
1981	.776	.289	.751	.997	.983
	(.004)	(.006)	(.004)	(.037)	(.009)

<u>Table 3</u>

Industry-Level Output Elasticities

	OLS ($\hat{\$}$)		Effect of Differencing: Proportion of Industries with		Effect of IV: Proportion of Industries with		IV/Firm Difference ($\tilde{\$}_{FD}$)	
	Median	IQR	$\hat{\$}_{TD} > \hat{\$}$	$\hat{\$}_{FD} > \hat{\$}$	$\tilde{\$}_{TD} > \hat{\$}_{TD}$	$\tilde{\$}_{FD} > \hat{\$}_{FD}$	Median	IQR
<u>Production Hours</u>								
1975	.822	.111	.010	.295	--	.914	.918	.120
1981	.803	.140	.011	.200	.867	.933	.930	.148
<u>Production Workers</u>								
1975	.811	.120	.010	.295	--	.895	.917	.125
1981	.793	.142	.011	.233	.878	.922	.930	.138
<u>Nonproduction Workers</u>								
1975	.818	.145	.010	.467	--	.933	.944	.137
1981	.806	.165	.011	.478	.944	.944	1.010	.154

Table 4

Own-Wage Elasticities of Labor Demand
(standard errors in parentheses)

	OLS $\hat{\beta}$	Time Difference $\hat{\beta}_{TD}$	Firm Difference $\hat{\beta}_{FD}$	IV/Time Difference $\tilde{\beta}_{TD}$	IV/Firm Difference $\tilde{\beta}_{FD}$
Production Hours					
1975	-.621		-.508		-.461
	(.011)		(.015)		(.017)
1981	-.609	-.499	-.485	-.486	-.567
	(.011)	(.016)	(.018)	(.017)	(.019)
Production Workers					
1975	-.607		-.522		-.440
	(.010)		(.013)		(.015)
1981	-.551	-.366	-.422	-.318	-.467
	(.011)	(.014)	(.018)	(.016)	(.018)
Nonproduction Workers					
1975	-.481		-.478		-.378
	(.009)		(.013)		(.014)
1981	-.546	-.512	-.497	-.488	-.463
	(.010)	(.010)	(.013)	(.010)	(.017)

Table 5

Industry-Level Own-Wage Elasticities

	OLS ($\hat{\$}$)		Effect of Differencing: Proportion of Industries with		Effect of IV: Proportion of Industries with		IV/Firm Difference ($\tilde{\$}_{FD}$)	
	Median	IQR	*$\hat{\$}_{TD}$* > *$\hat{\$}$*	*$\hat{\$}_{FD}$* > *$\hat{\$}$*	*$\tilde{\$}_{TD}$* > *$\hat{\$}_{TD}$*	*$\tilde{\$}_{FD}$* > *$\hat{\$}_{FD}$*	Median	IQR
Production Hours								
1975	-.624	.362	.324	.219	--	.562	-.485	.402
1981	-.611	.349	.400	.311	.552	.533	-.600	.400
Production Workers								
1975	-.604	.243	.171	.314	--	.410	-.407	.469
1981	-.553	.300	.211	.256	.713	.522	-.440	.393
Nonproduction Workers								
1975	-.473	.221	.410	.333	--	.238	-.387	.296
1981	-.533	.198	.400	.411	.678	.478	-.472	.348

Table A-1

Labor Demand Equation - Production Hours
(standard errors in parentheses)

Explanatory Variable	OLS Cross-Section		Long Difference 1981-1975		Firm Difference 1981		Firm Difference 1975	
	1981	1975	OLS	IV	OLS	IV	OLS	IV
Production Worker Wage	-.609	-.621	-.499	-.486	-.485	-.567	-.508	-.461
	(.011)	(.011)	(.016)	(.017)	(.018)	(.019)	(.015)	(.017)
Non Production Worker Wage	-.042	-.035	.003	.031	-.027	.014	-.034	.069
	(.008)	(.007)	(.008)	(.009)	(.013)	(.014)	(.010)	(.011)
Output	.775	.804	.366	.934	.713	.916	.775	.923
	(.003)	(.002)	(.005)	(.019)	(.004)	(.008)	(.003)	(.006)
Age Group 1 (start date < 1950)	.242	.281			.284	.394	.315	.501
	(.011)	(.010)			(.015)	(.016)	(.011)	(.013)
Age Group 2 (start date 1951-55)	.184	.196			.216	.317	.226	.403
	(.015)	(.014)			(.020)	(.021)	(.016)	(.019)
Age Group 3 (start date 1956-60)	.142	.155			.155	.291	.162	.356
	(.013)	(.012)			(.018)	(.019)	(.014)	(.017)
Age Group 4 (start date 1961-65)	.117	.093			.143	.256	.106	.277
	(.012)	(.011)			(.017)	(.018)	(.013)	(.015)
Age Group 5 (start date 1966-70)	.084	.048			.103	.173	.054	.149
	(.011)	(.010)			(.016)	(.016)	(.012)	(.014)

Age Group 6 (start date 1971-75)	.040				.046	.076		
	(.011)				(.016)	(.017)		
Price Electricity	-.161	-.081	-.027	-.053	-.134	-.073	-.102	-.109
	(.010)	(.007)	(.009)	(.010)	(.014)	(.014)	(.009)	(.010)
Ownership Dummy	.087	.072						
	(.008)	(.008)						
Sample Size	30,176	41,576	16,893	16,893	19,269	19,269	32,492	32,492

All regressions include dummy variables for four-digit SIC industry. IV regressions use four-digit industry dummies and a fourth-order polynomial in the plant's equipment capital stock and structures capital stock as instruments.

Table A-2

Labor Demand Equation - Production Workers
(standard errors in parentheses)

Explanatory Variable	OLS Cross-Section		Long Difference 1981-1975		Firm Difference 1981		Firm Difference 1975	
	1981	1975	OLS	IV	OLS	IV	OLS	IV
Production Worker Wage	-.551	-.607	-.366	-.318	-.422	-.467	-.522	-.440
	(.011)	(.010)	(.014)	(.016)	(.018)	(.018)	(.013)	(.015)
Non Production Worker Wage	-.047	-.038	.014	.042	-.024	.013	-.030	.070
	(.008)	(.007)	(.008)	(.009)	(.013)	(.014)	(.010)	(.011)
Output	.766	.798	.358	.929	.705	.904	.771	.917
	(.003)	(.002)	(.004)	(.033)	(.004)	(.008)	(.003)	(.006)
Age Group 1 (start date < 1950)	.241	.282			.285	.387	.319	.501
	(.011)	(.009)			(.015)	(.016)	(.016)	(.013)
Age Group 2 (start date 1951-1955)	.183	.196			.217	.314	.229	.402
	(.015)	(.014)			(.020)	(.021)	(.016)	(.018)
Age Group 3 (start date 1955-1960)	.141	.156			.157	.289	.167	.358
	(.013)	(.012)			(.018)	(.019)	(.014)	(.016)
Age Group 4 (start date 1961-1965)	.112	.091			.139	.247	.108	.276
	(.012)	(.011)			(.017)	(.018)	(.013)	(.015)
Age Group 5 (start date 1966-1970)	.080	.049			.102	.170	.057	.151
	(.011)	(.010)			(.016)	(.016)	(.012)	(.014)

Age Group 6 (start date 1971-1975)	.038				.044	.072		
	(.012)				(.016)	(.017)		
Price Electricity	-.167	-.084	-.028	-.054	-.141	-.079	-.105	-.112
	(.010)	(.007)	(.009)	(.010)	(.014)	(.014)	(.009)	(.010)
Ownership Dummy	.089	.069						
	(.008)	(.008)						
Sample Size	30,176	41,576	16,893	16,893	19,269	19,269	32,492	32,492

All regressions include dummy variables for four-digit SIC industry. IV regressions use four-digit industry dummies and a fourth-order polynomial in the plant's equipment capital stock and structures capital stock as instruments.

Table A-3

Labor Demand Equation - Nonproduction Workers
(standard errors in parentheses)

Explanatory Variable	OLS Cross-Section		Long Difference 1981-1975		Firm Difference 1981		Firm Difference 1975	
	1981	1975	OLS	IV	OLS	IV	OLS	IV
Production Worker Wage	.006	-.063	-.117	-.086	.120	.056	.003	.072
	(.014)	(.013)	(.019)	(.019)	(.018)	(.023)	(.018)	(.019)
Non Production Worker Wage	-.546	-.481	-.512	-.488	-.497	-.463	-.478	-.378
	(.010)	(.009)	(.010)	(.010)	(.013)	(.017)	(.013)	(.014)
Output	.776	.800	.289	.997	.751	.983	.788	.953
	(.004)	(.003)	(.006)	(.037)	(.004)	(.009)	(.004)	(.007)
Age Group 1 (start date < 1950)	.278	.261			.318	.418	.288	.465
	(.014)	(.012)			(.015)	(.020)	(.015)	(.016)
Age Group 2 (start date 1951-55)	.170	.171			.192	.287	.184	.352
	(.019)	(.018)			(.020)	(.026)	(.021)	(.023)
Age Group 3 (start date 1956-1960)	.142	.133			.174	.303	.131	.320
	(.017)	(.016)			(.018)	(.024)	(.019)	(.020)
Age Group 4 (start date 1961-1965)	.081	.080			.104	.214	.067	.235
	(.016)	(.015)			(.017)	(.022)	(.017)	(.019)
Age Group 5 (start date 1966-1970)	.055	.009			.066	.132	.001	.093
	(.015)	(.014)			(.016)	(.021)	(.016)	(.017)

Age Group 6 (start date 1971-1978)	.012				.019	.045		
	(.015)				(.016)	(.021)		
Price Electricity	.042	.062	.019	.000	.056	.130	.044	.044
	(.013)	(.009)	(.011)	(.012)	(.014)	(.018)	(.012)	(.013)
Ownership Dummy	.057	-.038						
	(.011)	(.010)						
Sample Size	30,176	41,576	16,893	16,893	19,269	19,269	32,492	32,492

All regressions include dummy variables for four-digit SIC industry. IV regressions use four-digit industry dummies and a fourth-order polynomial in the plant's equipment capital stock and structures capital stock as instruments.

Table 1

Sample Summary Statistics of Plant Employment: Mean and Standard Deviation

Year	Mean of log employment: Production Hours (thousands)	Mean of log employment: Production Workers	Mean of log employment: Nonproduction Workers	Standard Deviation of log employment: Production Hours (thousands)	Standard Deviation of log employment: Production Workers	Standard Deviation of log employment: Nonproduction Workers
Cross Section Data Sets						
1975	4.97	4.31	3.10	1.36	1.36	1.44
1981	5.22	4.55	3.42	1.32	1.31	1.43
Time Difference Data Set						
1975	5.80	5.13	3.90	1.13	1.13	1.32
1981	5.86	5.19	4.02	1.11	1.11	1.30
Firm Difference Data Sets						
1975	5.12	4.45	3.24	1.37	1.37	1.46
1981	5.64	4.97	3.82	1.26	1.26	1.42