THE LONG-RUN DEMAND FOR SKILLED AND UNSKILLED LABOR IN COLOMBIAN MANUFACTURING PLANTS

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Abstract—This note estimates the long-run demand for skilled and unskilled labor using panel data for Colombian manufacturing plants. Unobserved heterogeneity and measurement error problems that commonly arise in microdata production estimates are examined. Output measurement errors cause OLS estimators to underestimate the output and wage response of employment demand. Time-difference estimators exaggerate the measurement error biases. Instrumental-variable estimates of the output elasticities are 0.89 and 0.76 and own-wage elasticities are −0.42 and −0.65 for skilled and unskilled labor, respectively. The output elasticity is larger for skilled labor whereas the wage elasticity is larger for unskilled labor in virtually every industry.

I. Introduction

Despite its small size, the manufacturing sector in many developing countries is a major source of modern sector employment in general, and skilled labor employment in particular. A wide range of government activities affect labor market outcomes by altering the employers' demand for workers. Demand-side policies, including minimum wages, requirement that employers provide nonwage amenities such as retirement benefits or health care, employer taxes to fund social security systems, wage indexation policies, and severance pay requirements, all alter the cost of hiring workers and can thus impact manufacturing sector employment.

Although much of the analysis of labor supply issues in developing countries has been conducted at the micro level, the empirical literature on labor demand in developing countries is almost exclusively limited to cross-country or intertemporal comparisons at the industry or aggregate level.[1] As a result, there is virtually no direct evidence on how individual firms or plants adjust employment in response to changes in the cost of labor or the demand for their output.

This note provides an empirical study of the plant-level demand for skilled and unskilled labor in the Colombian manufacturing sector and focuses on estimation of the own-price and output elasticities. While the estimation of labor demand functions with microdata raises some unique econometric issues, it provides several advantages over estimates based on industry or aggregate data. Elasticities estimated using microdata are less likely than aggregate studies to suffer from simultaneity bias. To the extent that the supply of labor to a single plant can be viewed as perfectly elastic, the endogeneity of wages at the plant level is not a problem. Furthermore, demand elasticities estimated from plant-level data measure more accurately the response of individual producers to exogenous wage changes than elasticities estimated from industry-level data. The latter also reflect changes in employment resulting from the exit and entry of plants to the industry.

The empirical work utilizes microdata for a panel of plants that was collected as part of the Colombian manufacturing census for the years of 1981 through 1987. The data allow the measurement of plant-level wages and employment for both skilled and unskilled workers, rather than the more common production–nonproduction worker breakdown.[2] They also allow measurement of the full cost of workers in the plant, including mandated and voluntary fringe benefits and other wage supplements. The empirical model controls for observable producer heterogeneity arising from differences in plant ownership type, age, output, and whether the plant participates in the export market. Several econometric techniques are used to control for unobserved heterogeneity and output measurement error problems that frequently arise when using establishment data to estimate production models.

The empirical estimates of the labor demand functions reveal substantial adjustment in the employment of skilled and unskilled workers at the plant level in response to differences in wages, output, and other observable plant characteristics. The estimates are sensitive to corrections for output measurement error. The demand for skilled workers is found to be less elastic than the demand for unskilled workers, while the output response of skilled labor is greater than that of unskilled labor.

The following section outlines an empirical model of a plant's demand for skilled and unskilled labor and describes the data and variables. Section III discusses the econometric specification. The empirical results are contained in section IV and section V concludes.

II. Empirical Model of Plant Demand for Labor

Assume that each plant's production function can be represented by a value-added output function which has as its arguments inputs of skilled labor L^s, unskilled labor L^u, capital services K, and an index of the plant's technology A. Each plant chooses the capital and labor inputs to minimize the cost of producing a planned level of output Q^*. This gives rise to conditional labor demand functions whose arguments are the full cost of an additional skilled and unskilled worker W^s and W^u, the price of capital services W^k, planned output Q^*, and the plant's technology A.

To develop an empirical model of labor demand several data issues must be addressed. As is true in most establishment survey data sets, it is not possible to measure the plant's price of capital services. Because much of the variation in the panel data set we utilize is cross sectional, much of the differences in plant-level service prices for capital will result from differences in the opportunity cost of funds. To approximate these differences we include a dummy variable (*CORP*) that

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[1] For a survey of labor market research in developing countries see Squire (1981). Hamermesh's (1993) comprehensive review of the empirical labor demand literature indicates that only a small proportion of the labor demand studies have been based on establishment-level microdata. Only the study by Sosin and Fairchild (1984) uses microdata on manufacturing producers in a developing country.

[2] Hamermesh (1993, table 3.7) indicates that virtually all studies of the demand for heterogeneous labor have disaggregated workers into production or nonproduction categories, and have used industry-level time-series data. What is missing from the literature to date are labor demand estimates based on microdata for producers that disaggregate labor by skill groups.

takes the value 1 if the plant is owned by a corporation and 0 if owned by a proprietorship or partnership. The latter categories generally have smaller plants and more limited access to formal capital markets.[3]

We approximate the plant's technology index A with a group of observable plant characteristics. The plant's age (AGE) controls for vintage effects in the plant's technology as well as for differences in plant efficiency.[4] A dummy variable that equals 1 if the plant exports any of its output in the sample year (EXP) is included to control for possible differences in the quality or type of output produced by exporting plants. Year dummy variables D_t control for time-period-specific shocks common to all plants in the industry. Region dummies D_r are included to control for differences in local labor markets.

The empirical demand equations for skilled and unskilled workers by plant i year t are

$$\begin{aligned}\ln L^s_{it} &= \beta^s_0 + \beta^s_1 \ln W^s_{it} + \beta^s_2 \ln W^u_{it} + \beta^s_3 \ln Q^*_{it} + \beta^s_4 AGE_{it} \\ &\quad + \beta^s_5 CORP_{it} + \beta^s_6 EXP_{it} + \alpha^s_t D_t + \alpha^s_r D_r + \eta^s_{it} \\ \ln L^u_{it} &= \beta^u_0 + \beta^u_1 \ln W^u_{it} + \beta^u_2 \ln W^s_{it} + \beta^u_3 \ln Q^*_{it} + \beta^u_4 AGE_{it} \\ &\quad + \beta^u_5 CORP_{it} + \beta^u_6 EXP_{it} + \alpha^u_t D_t + \alpha^u_r D_r + \eta^u_{it}.\end{aligned} \tag{1}$$

All coefficients are allowed to differ in the two labor demand equations, thus allowing different price and output responses for skilled and unskilled workers.

The data consist of observations on the individual plants in the Colombian manufacturing sector for the years of 1981 through 1987. The data are drawn from the yearly census of manufacturing establishments and cover all plants with 10 or more employees that operate in any of 17 three-digit SITC industries.[5] Observations in the cross-section data sets have been matched over time to form a plant-level panel data set, which is described in Roberts (1996).

The Colombian census only collects information on the number of workers, not on the hours worked. While fluctuations in hours per worker are crucial for understanding short-run labor demand, variation in the number of workers is the primary adjustment method in the long run. Our focus on employment, rather than hours adjustment, is consistent with our objective of explaining long-run labor demand differences at the plant level. The skilled labor input is constructed as a weighted sum of the number of workers reported in three census categories: skilled workers, local technicians, and foreign technicians. The weights used are the full wage (average salaries plus benefits per worker) of each category relative to the full wage of the skilled worker category. The average full wage of this skilled labor aggregate is constructed by dividing the total expenditure on salaries and benefits for the three skill groups by the skilled labor aggregate.[6] The number of unskilled workers and their average full wage is constructed in a similar way as a weighted aggregate over two census skill classes: unskilled workers and apprentices.

The output of the plant is defined as real value added. It is constructed as nominal value added, which equals the value of sales plus changes in final goods inventories minus the cost of intermediate materials, deflated by an industry-specific output price index. The plant's capital stock, which will be used as an instrumental variable, is measured as the sum of the book value of structures, equipment, and land at the beginning of each year.

III. Econometric Specification

The appropriate estimator for the labor demand equations depends on the source of the error terms η^s_{it} and η^u_{it} in equations (1). When using establishment data to estimate production and factor demand models there are three potentially important sources of error. The first is plant heterogeneity, which can arise from the nonobservability of some key inputs in the production process, such as managerial efficiency or technical knowledge, vintage of capital equipment, the quality of plant output, or the plant's service price of capital. These will be treated as plant-specific components in the disturbance, μ^m_i ($m = s, u$). If the plant-specific component is known to the plant owners, then it is likely to lead to a permanent observable difference in plant output, employment, and wages. Failure to recognize this can lead to simultaneity bias in labor demand equations estimated from establishment data.[7]

The second source of error arises from year-to-year fluctuations in establishment output as a result of unforeseen fluctuations in demand, factor supplies, equipment breakdowns, or 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. The appropriate output variable to include in the labor demand equations is the plant's planned output $\ln Q^*_{it}$. Assume ν_{it} is a zero-mean constant-variance measurement error that is uncorrelated with the plant's planned output. The observed output of the plant, which is used as the regressor in equations (1), can be written as $\ln Q_{it} = \ln Q^*_{it} + \nu_{it}$.[8]

The final source of error is pure random shocks to the labor demand equation that vary across plants and over time. This will be denoted by ϵ^m_{it}. Recognizing these three sources of random variation implies that

[3] Tybout (1983, 1984) studies the pattern of access to capital markets by manufacturing firms in Colombia and finds that interest controls place severe constraints on the ability of small firms to borrow in capital markets. This results in small firm investment being determined almost exclusively by their earnings and contributes to their more labor-intensive production.

[4] Jovanovic's (1982) model of industry evolution predicts that plant age and efficiency will be positively correlated. Liu and Tybout (1996) compare productivity across plants in Colombia and Chile and find that entering and exiting cohorts have lower average productivity than cohorts of older, surviving producers.

[5] Several industries were deleted from the analysis because they contained too few plant observations to allow the full range of econometric models to be estimated. The included industries account for between 90.0 and 93.5% of annual manufacturing employment. We also eliminated a small number of plants that are government owned, collectives, or cooperatives.

[6] Nonwage benefits, as a share of the full wage, have increased over time from approximately 0.32 in 1978 to 0.45 in 1989. Nonwage costs are also more important for large plants, rising from 0.27 of full costs of plants with 10–19 employees to 0.44 for plants with at least 250 employees.

[7] This point has been widely discussed in the literature. Tybout and Westbrook (1995) provide a summary of the effect of unobserved heterogeneity on scale estimates using both production function and cost function or factor demand models.

[8] Measurement error could also exist in the average plant wage if, for example, there are overtime premiums and large fluctuations in overtime hours in response to demand shocks. We were unable to develop satisfactory instruments for plant wages, or the change in wages. All attempts to correct for this problem resulted in very imprecise parameter estimates because of the poor quality of instruments. In this note we only discuss output measurement errors because we were more successful in dealing with this problem.

the error terms in the labor demand equations can be written as

$$\begin{aligned} \eta_{it}^{s} &= \mu_i^{s} - \beta_3^{s}\nu_{it} + \epsilon_{it}^{s} \\ \eta_{it}^{u} &= \mu_i^{u} - \beta_3^{u}\nu_{it} + \epsilon_{it}^{u} \end{aligned} \tag{2}$$

where β_3^m is the coefficient on the output in the demand equation for labor type m. 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. It is possible to identify the likely direction of the bias in the own-price (β_1^s and β_1^u) and output (β_3^s and β_3^u) elasticities. In the case of unobserved efficiency differences among plants, high values of μ_i denote inefficient plants so μ_i will be positively correlated with employment but negatively correlated with output and wages.[9] This will result in a negative bias in both the output and the own-price elasticities. Thus OLS will tend to underestimate the plant's employment response to output changes and overestimate the response to wage changes.

The correlation between ν_{it} and the actual output level that results from measurement error also biases OLS output elasticities toward zero. Output measurement error can also bias the estimates of own-price elasticities. Griliches (1986, p. 1479) shows that the bias in the coefficient for the error-ridden variable is transmitted to other coefficients with the opposite sign.[10] This will bias the own-price elasticities toward zero, with the magnitude of the bias increasing as the correlation between output and wages rises. As a result of output measurement error, OLS will tend to underestimate the price responsiveness of employment to both wage and output changes.

To correct the possible correlation betwen the plant's observed output level in $\ln Q_{it}$ and the errors ν_{it} and μ_i^m we utilize both instrumental-variables (IV) and time-difference (TD) estimators. The instrumental-variables estimator requires an instrument that is correlatd with the planned output of the plant but uncorrelated with the random fluctuations to output, and the plant's beginning-of-year capital stock satisfies this requirement.[11] To correct for plant-specific heterogeneity we utilize time-difference estimators.

While the time-difference transformation corrects one potential problem, Griliches (1986) and Griliches and Hausman (1986) demonstrate that it can exaggerate the bias due to measurement error by reducing the amount of systematic variation in the data. The bias is likely to be more severe the shorter the time differences used. We utilize time differences that vary from 1 to 6 years. In this application it is likely that the observations on actual plant output provide better measures of the level of planned output than the growth in planned output, and thus the measurement error bias is likely to be more severe when the equations are expressed in time differences.[12] Finally, to correct for both unobserved heterogeneity and measurement error we apply instrumental-variables estimators to the time-differenced data. The change in output is instrumented with the plant's capital stock in both years over which the difference is taken. The capital stocks are also interacted with the exogenous variables in the model.[13]

TABLE 1.—LABOR DEMAND BY SKILL GROUP: POOLED-INDUSTRY ESTIMATES

Variable	OLS	IV
	Skilled Worker Labor Demand	
$\ln W^s$	−0.279 (25.06)[a]	−0.423 (34.01)[a]
$\ln W^u$	−0.134 (9.89)[a]	−0.273 (18.51)[a]
$\ln Q$	0.733 (173.58)[a]	0.894 (128.11)[a]
AGE	0.005 (13.36)[a]	0.003 (8.62)[a]
EXP	0.144 (10.76)[a]	0.001 (0.03)
CORP	0.293 (20.58)[a]	0.139 (9.05)[a]
R^2	0.736	0.726
Sample size	32,971	32,689
	Unskilled Worker Labor Demand	
$\ln W^s$	0.047 (5.50)[a]	−0.034 (3.58)[a]
$\ln W^u$	−0.564 (53.89)[a]	−0.650 (57.63)[a]
$\ln Q$	0.661 (202.19)[a]	0.755 (141.55)[a]
AGE	0.006 (24.15)[a]	0.006 (20.63)[a]
EXP	0.079 (7.58)[a]	−0.002 (0.18)
CORP	0.012 (1.11)	0.080 (6.79)[a]
R^2	0.746	0.742
Sample size	32,971	32,689

Notes: All equations contain a constant term, 6 year dummies, 16 standard industrial classification dummies, and 5 region dummies. The excluded variables used to instrument $\ln Q$ are $\ln K$, $(\ln K)^2$, and their interactions with the plant wages and plant characteristics. Absolute values of t-statistics are in parentheses.

[a] Implies significantly different from zero at the 5% significance level.

IV. Empirical Results

We begin by reporting labor demand estimates that pool plants across industries and include industry dummy variables in the regressions. These pooled-industry estimates illustrate the basic econometric issues and biases clearly. Separate industry estimates are discussed below. The results for the OLS estimator are reported in the first column of table 1. For skilled workers the own-wage elasticity is −0.279, whereas for unskilled workers it is −0.564. The output elasticities for the skilled and unskilled groups are 0.733 and 0.661, respectively.

To address the potential problem of output measurement error that biases the OLS wage and output elasticities toward zero we report instrumental-variables estimates of the demand equations in column 2 of table 1. A clear pattern is evident: the own-wage elasticities increase in absolute value, to −0.423 for skilled workers and to −0.650 for unskilled workers, and the output elasticities both increase, to 0.894 for skilled and to 0.755 for unskilled workers. These movements suggest that output measurement error is a significant sources of bias

[9] 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).

[10] This will be true if the variable not subject to measurement error is positively correlated with the observed, error-ridden variable. Wages and output are strongly positively correlated in our data, so that output measurement error should result in a positive bias in the own-price elasticity.

[11] The use of beginning-period capital stocks also removes simultaneity problems that arise if a profit-maximizing firm jointly chooses both output and labor inputs each period.

[12] The wage elasticities are also likely to be biased toward zero, but the magnitude of the bias now depends on the correlation between output growth and wage growth, and it is not clear how substantial this will be.

[13] Griliches and Hausman (1986) demonstrate that when panel data are available, lead or lag values of the variable subject to measurement error may be appropriate instrumental variables. Tybout and Westbrook (1993) apply this methodology to the estimation of scale economies. We utilized levels of output in other years as instruments, but they had little effect on our estimates.

TABLE 2.—OUTPUT AND OWN-WAGE ELASTICITIES USING TIME-DIFFERENCE ESTIMATORS

	First Difference	Second Difference	Third Difference	Fourth Difference	Fifth Difference	Sixth Difference	Sixth Difference/IV
			Skilled Worker Labor Demand				
Output	0.183 (32.61)	0.264 (38.58)	0.333 (40.34)	0.367 (36.66)	0.420 (31.79)	0.457 (23.29)	0.783 (14.17)
Own wage	−0.311 (39.92)	−0.326 (32.19)	−0.324 (25.22)	−0.310 (19.09)	−0.297 (13.94)	−0.333 (10.05)	−0.434 (11.30)
			Unskilled Worker Labor Demand				
Output	0.204 (50.54)	0.270 (53.69)	0.303 (48.27)	0.321 (40.96)	0.354 (33.73)	0.428 (29.10)	0.586 (14.61)
Own wage	−0.457 (65.74)	−0.521 (55.43)	−0.560 (44.91)	−0.577 (36.00)	−0.564 (25.61)	−0.578 (18.12)	−0.644 (17.80)
Sample size	24,380	17,922	12,774	8613	5136	2367	2367

Note: Absolute values of t-statistics are in parentheses.

in OLS estimates of the wage and output elasticities. A Hausman test that the error term in equations (1) is uncorrelated with the plant's output lends further support to this conclusion. In both labor demand equations we reject the no-correlation assumption that underlies the OLS estimator.

In order to examine the possible bias resulting from unobserved heterogeneity, we estimate a number of time-difference models. The results of first through sixth time differences are reported in table 2. All of the estimates control for time-invariant fixed effects, but the shorter time differences should be subject to more downward bias in the output elasticities. The pattern of output coefficients is consistent with this. As we move from first to sixth time differences the output elasticity for skilled labor demand increases monotonically from 0.183 to 0.457 and for unskilled labor it rises from 0.204 to 0.428. The wage elasticities also show a systematic change for unskilled labor, with the elasticity changing from −0.457 to −0.578 as the time difference increases. There is no systematic change in the wage elasticity for skilled workers with the length of time differencing.

In all cases, even the long time differences, the output elasticity estimates indicate an implausibly high degree of returns to labor. The finding that differencing the data results in implausibly small coefficients is a common one in the applied production literature (see Griliches and Mairesse (1984), Mairesse and Dormont (1985), Griliches and Hausman (1986), Mairesse (1990), Tybout and Westbrook (1993, 1995), and Dunne and Roberts (1994)). Measurement error in output, which is exaggerated when time differences are used, is the most likely explanation.[14]

To control for both measurement error and unobserved heterogeneity we estimate the time-differenced model using the plant's initial- and ending-period capital stock as instruments for output growth. The results for the sixth difference/IV estimator are reported in the last column of table 2. The output elasticity increases for both labor categories when compared with the noninstrumented version, suggesting that measurement error problems persist even with the long time differences.[15] The final estimates of the output elasticity are 0.783 for skilled workers and 0.586 for unskilled. The standard errors of the estimates also increase substantially as a result of differencing. Overall, the output elasticity estimates change in a direction that is consistent with measurement error problems, but even after instrumenting with capital stock variables the output elasticities appear to be quite small.[16]

In contrast the own-wage elasticities from the time-differenced instrumental-variables estimates are virtually identical to the instrumental-variables estimates reported in table 1. The two estimates are −0.434 and −0.423 for skilled workers and −0.644 and −0.650 for unskilled workers. Thus corrections for unobserved heterogeneity have little effect on wage elasticities. The coefficients indicate that the demand for unskilled workers is substantially more elastic than the demand for skilled workers.

The patterns revealed in the pooled data also characterize estimates at the industry level (see Roberts and Skoufias (1994) for a complete set of estimates). Instrumental-variables estimates of the output elasticities for skilled labor vary from 0.752 to 1.061 across industries with a median value of 0.874. In every industry instrumental-variables estimates are larger than the OLS estimates. In five cases we do not reject the hypothesis of constant returns to skilled labor. The instrumental-variables estimates for unskilled labor vary from 0.520 to 0.862 with a median value of 0.798. These estimates still indicate increasing returns to unskilled labor, and the hypothesis of constant returns ($\beta_3^u = 1$) is rejected in each of the 17 industries.

The instrumental-variables estimates of the own-wage elasticity vary substantially across industries, particularly for skilled labor. The price elasticities for skilled labor are significantly different from zero in all but one industry. The significant estimates vary from a low of −0.186 to a high of −0.904, with a median of −0.385. For unskilled workers the estimates vary from −0.167 to −0.759, with a median estimate of −0.652. While there is substantial variation across

[14] A second explanation is that selection bias due to plant failure is a problem in the time-differenced data. When using an estimator based on a time difference of k years we use data on only those plants that are present for $k + 1$ consecutive years. We can informally check if selection bias is a problem by comparing cross-section estimates using only the sample of plants present for 2, 3, . . . , 7 consecutive years. In every case the cross-section OLS estimates on these different samples of surviving plants are very similar to the estimates using all plants reported in table 1. The changes in coefficients observed in table 2 do not appear to reflect differences in the labor demand function between surviving and failing plants.

[15] We also constructed instrumental-variables estimates for the shorter time differences. The instrumental-variables estimate for each time difference is greater than the noninstrumented estimate, and the instrumental-variables estimates increase as longer differences are used.

[16] This is the one major difference between the findings of this note and the estimates reported by Dunne and Roberts (1994) using U.S. establishment data. They find that instrumental-variables estimates of long time differenced data produce output elasticity estimates of 0.93 for production workers and production hours and 1.0 for nonproduction workers.

industries, in all but three industries the demand for unskilled workers is more elastic than that for skilled workers, reflecting the finding from the pooled data estimates.

V. Conclusion

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 note we utilize a microdata set of Colombian manufacturing plants to estimate demand functions for skilled and unskilled labor. The output and wage elasticity estimates correspond to the employment response of individual producers, and not the market- or sector-level response, to exogenous changes in output demand or factor prices. The price of labor is measured as the full cost of a worker, including nonwage benefits paid by the employer as well as wages and salaries. Several econometric techniques are used to correct for possible unobserved heterogeneity and measurement error in output, and the sensitivity of estimates to these corrections is analyzed. The latter appears to be particularly important in this data set, mirroring a finding of Dunne and Roberts (1994) using U.S. establishment data.

The magnitude and the statistical signficance of the parameters indicate that there is substantial adjustment of employment at the plant level in response to differences in output, wages, or other plant characteristics. One of the strengths of the data set we utilize is that the demand curves for skilled and unskilled labor can be distinguished. Comparison of the output and price elasticities for the two groups reveals that this distinction is important. Focusing on the instrumental-variables estimates using the pooled data, the own-price elasticity is −0.423 for skilled labor and −0.650 for unskilled. A higher price elasticity for unskilled labor is also found in 14 of the 17 industries.[17] This implies that an equal proportional increase in the full cost of each type of worker will result in a larger decline in the employment of unskilled workers. This comparison is particularly relevant for Colombia, where labor market policy in recent years has had a major impact on the provision of nonwage benefits, with many of the required payments expressed as a proportion of wages or salaries. Further increases in mandatory nonwage payments, assuming they are not fully offset by reductions in wages, would tend to shift the employment mix toward skilled labor while reducing overall employment in existing manufacturing plants.

The pooled instrumental-variables estimates of the output elasticity for skilled and unskilled labor are 0.894 and 0.755, respectively. The output elasticity for skilled labor equals or exceeds the elasticity for unskilled labor in 16 of the 17 industries. In 14 industries the skilled labor output elasticity exceeds 0.840. Given that these estimates are largely based on cross-sectional variation in the data, they imply that, as we move across the size distribution of producers, skilled labor employment increases roughly in proportion to plant output in most industries. In contrast, as we move toward larger plants, employment of unskilled labor increases at a slower rate than output, thus reflecting the fact that larger plants tend to have higher ratios of skilled to unskilled workers.

Overall, estimates of long-run labor demand equations using microdata indicate a more significant output response than is generally reported using sectoral or aggregate data. The own-wage elasticities are also substantially larger for unskilled labor, exceeding −0.600 in 11 of 17 industries, than aggregate data imply. Thus the employment response at the microlevel to changes in output or factor prices is sizable.

[17] The higher price elasticity for unskilled labor holds in virtually all industries regardless of whether the OLS, instrumental-variables, or time-difference estimators are used. While empirical studies based on disaggregated skill groups are uncommon, Hamermesh (1993, table 3.7) reports that several studies have found that the demand for blue collar or production workers is more elastic than the demand for white-collar or nonproduction workers.

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[Footnotes]

[3] **Interest Controls and Credit Allocation in Developing Countries**
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[4] **Selection and the Evolution of Industry**
Boyan Jovanovic
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[9] **Selection and the Evolution of Industry**
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[9] **The Employer Size-Wage Effect**
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