NBER WORKING PAPER SERIES

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Working Paper 7846
http://www.nber.org/papers/w7846

NATIONAL BUREAU OF ECONOMIC RESEARCH
1050 Massachusetts Avenue
Cambridge, MA 02138
August 2000

I would like to thank Eric Edmonds, Gene Grossman, Penny Goldberg, Bo Honore and the participants at the international brownbag lunch at Dartmouth for many helpful comments. The views expressed herein are those of the author and not necessarily those of the National Bureau of Economic Research.

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ABSTRACT

Although many developing countries have experienced growing income inequality and an increase in the relative demand for skilled workers during the 1980s, the sources of this trend remain a puzzle. This paper examines whether investment and adoption of skill-biased technology have contributed to within-industry skill upgrading using plant-level data from Chile. Using semiparametric and parametric approaches, I investigate whether plant-level measures of capital and investment, the use of imported materials, foreign technical assistance, and patented technology affect the relative demand for skilled workers. I find positive relationship between these measures and skill upgrading. Capital deepening and the adoption of skill biased technology therefore might contribute to the increased relative demand for skilled workers within industries.

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What explains skill upgrading in less developed countries?

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Abstract

Although many developing countries have experienced growing income inequality and an increase in the relative demand for skilled workers during the 1980s, the sources of this trend remain a puzzle. This paper examines whether investment and adoption of skill-biased technology have contributed to within-industry skill upgrading using plant-level data from Chile. Using semiparametric and parametric approaches, I investigate whether plant-level measures of capital and investment, the use of imported materials, foreign technical assistance, and patented technology affect the relative demand for skilled workers. I find positive relationship between these measures and skill upgrading. Capital deepening and the adoption of skill biased technology therefore might contribute to the increased relative demand for skilled workers within industries.

JEL Classification: F16, J31, O15
Keywords: Skill upgrading; Skill biased technology; Technology transfers

1. Introduction[*]

During the 1980s, many developing countries such as Chile, Mexico, Costa Rica, and Uruguay experienced an increase in income inequality in favor of skilled workers and an increase in the relative demand for skilled labor, i.e. skill upgrading (Robbins (1996)). Growing demand for skilled workers and increased income inequality based on workers' skills present a particularly severe problem for societies in developing countries: they precipitate the negative social consequences associated with higher initial poverty levels and income disparities. Since little is known about the sources of skill upgrading in developing countries, this paper investigates the relationship between growing demand for skilled labor, investment, imported materials, and technology adoption using plant level data in Chile.

This study is motivated by two issues. First, the relationship between skill upgrading and plant investment, use of imported materials, and technology adoption may be important to understanding growing income inequality in many less developed countries. Several well documented facts suggest that less developed countries have experienced an upward shift in their relative demands for skilled workers. First, income inequality between skilled and unskilled workers increased in countries such as Mexico, Chile, and Costa Rica after trade liberalization (Harrison and Hanson (1995, 1999, 1999a), Revenga (1997), Robbins (1995, 1996)). Second, most of the worker reallocation occurred within rather than across industries (Harrison and Hanson (1995), Robbins (1995, 1996)). Moreover, the share of skilled labor in total industry employment increased concurrently with an increase in the skill-premium (Harrison and Hanson (1995), Robbins (1995, 1996)). These patterns cannot be explained by the strengthening of product-level import competition from developed countries after trade liberalizations.[1]

[*] I would like to thank Eric Edmonds, Gene Grossman, Penny Goldberg, Bo Honore and the participants at the international brownbag lunch at Dartmouth for many helpful comments.

[1] Increased exposure to trade from relatively skilled-labor abundant developed countries should, through product demand changes, decrease relative wages of the skilled workers and lead to workers reallocation *across* industries. Hanson and Harrison (1999a) provide an appealing product-market based explanation for the increased income inequality in Mexico. They show that industries that employed unskilled labor relatively intensively had higher rates of protection before trade liberalization. Therefore, by Stolper-Samuelson theorem, the decrease in price of the goods that are relatively unskilled labor intensive, should lead to increased income inequality based on skills. This explanations, however, still does not account for the lack of reallocation of labor across industries, and the concurrent rise in skill premium and employment share of skilled workers.

Although these labor market changes have been well documented, only two studies reviewed later (on Mexico) attempt to explain the sources of increased within industry relative demand for skilled workers in less developed countries.

A second motivation for my study is to explore whether skill upgrading that is related to plant investment, use of imported materials, and technology adoption occurs in all plants within an industry or whether it only occurs in a specific set of plants. The recent industrial organization literature emphasizes the importance of plant heterogeneity within industries (Olley and Pakes (1996), Roberts and Tybout (1996)). Yet, most studies on skill upgrading in developed countries rely on industry or individual worker level data. They obtain a positive correlation between skill upgrading and various measures of technology use, but they cannot distinguish whether skill upgrading is a general phenomena or whether it takes place only in certain plants within an industry.[2] On the other hand, a study by Doms, et. al. (1997) based on U.S. plant level panel data finds no evidence that the adoption of new technology is skill-biased after controlling for plant fixed effects. My plant level data presents a good setting to investigate the sources of skill upgrading in the case of Chile. The data provide information on plant ownership structure and workforce characteristics allowing me to control for plant-specific characteristics that could be driving the cross-sectional correlation between skill upgrading and various technology measures.

Growing income inequality in Chile has been documented before. Using household data from 1957 to 1992, Robbins (1995) shows first that, most of the growing income inequality between skill groups stems from demand rather than supply shocks to the labor market and second, that increases in the relative demand for skilled workers occurred within industries. He concludes that skill biased technological change might explain the observed patterns. Unfortunately, household data do not provide the direct measures of technology and detailed industry classification necessary to examine this issue

[2] Several studies on the United States obtain a positive link between skill upgrading and investment in R & D (Berman, Bound and Griliches (1994), Bernard and Jones (1999), Machin and Van Reenen (1998)), the use of computers at work (Berman, Bound, and Griliches (1994), Autor, et. al. (1998)), exporting (Bernard and Jones (1999)), and outsourcing (Feenstra and Hanson (1996)). Berman, Bound and Machin (1998) and Machin and Van Reenen (1998) confirm these results for a large group of developed countries.

closer. I therefore use plant-level data to explore this demand shift further. The Chilean data provide information on a plant's capital and investment, imported materials, foreign technical assistance, and the use of patented technology. If these measures are associated with new technologies that are skill-biased, they could contribute to the increasing demand for skilled workers.

To address the topic, I first compare the distribution of the relative share of skilled workers employed in plants with and without new investment, imported materials, and new technologies using **a** semiparametric methodology developed by DiNardo, et. al. (1996). Working with the entire distribution of the share of skilled workers in plants allows me to explore differences across plants that are not apparent when focusing on means or medians. One can, for example, observe where in the distribution of plants new investment and technology exert the biggest influence. Second, I consider skill upgrading by deriving a plant's demand for skilled labor in the context of a cost function. Finally, I specify a production function to derive the reduced form for relative plant-level employment and relate employment to plant characteristics. In the parametric part of my analysis, I allow plants that invest or use technology to employ a different mix of workers than plants that do not. A difficulty with the interpretation of the results in skill upgrading literature is that the variables representing skill biased technology could simply proxy for an omitted plant characteristic that affects relative demand for skilled labor and a plant's choice of technology use. I exploit the available data to control for plant-specific characteristics such as financial constraints and workforce composition other than skill that could affect plant technology and hiring decisions but have not been explicitly considered in previous studies.

Increases in the relative demand for skilled workers could be driven by several factors. First, firm demand for skilled workers might increase as a result of higher firm investment if capital and skilled labor are complements. Firms could invest more into new machinery and equipment if increased foreign competition forces them to improve their production process or they are able to import previously unavailable machinery from abroad. For example, the imports of machinery and equipment rose from US$267 to US$797 million from 1975 to 1981 after trade liberalization in Chile (Edwards and Edwards

(1987)). Second, increased income inequality in many developed countries may stem from skill-biased technological change (Author and Katz (1998), Berman, Bound, and Machin (1998)).[3] Adoption of skill-biased technology could also explain the growing demand for skilled labor in developing countries. Lower trade barriers expedite this process. Eaton and Kortum (1996, 1997) model how the benefits of innovation spread from one country to another through diffusion of technology or through the exchange of goods. They find that the impact of diffusion of knowledge on productivity depends on the proximity of a country to the technology source, tariff levels, and the flexibility of the domestic labor force. If the adoption of new technology requires relatively more skilled labor, technology adoption could explain the increase in the relative demand for skilled workers within industries in developing countries.

The existing studies of skill upgrading in less developed countries have mostly considered the impact of foreign direct investment (FDI) as a channel for the spread of technology across countries. Feenstra and Hanson (1997) and Hanson and Harrison (1999) find a positive link between FDI and skill upgrading in Mexico. Yet, the evidence on the relationship between the adoption of new technology, investment, or imported materials and skill upgrading independent of FDI is weaker. Hanson and Harrison (1999) find that firms obtaining technology through licensing agreements and import materials hire more skilled workers. However, Hanson and Harrison (1999) obtain a negative or insignificant relationship for other measures of investment and technology change.

In this study, I find a positive relationship between skill upgrading and imported materials, foreign technical assistance, and patent use. Moreover, I find evidence of capital-skill complementarity: the capital intensity of a plant is positively correlated with skill upgrading across all specifications. The increasing average investment of Chilean manufacturing plants during my sample could partially explain the growing demand for skilled labor in Chile. A positive correlation between other measures of technology and skill upgrading is robust to controls for plant heterogeneity and plant random effects, but

[3] This literature continues to disagree whether the labor demand shifts that changed the structure of wages resulted from the increased exposure to imports from developing countries, skill-biased technical change, or outsourcing.

the positive correlation becomes statistically insignificant when I account for unobserved plant heterogeneity with plant fixed effects. This might suggest that only certain plants acquire technology through patents, import materials, or use foreign technical assistance and these plants employ relatively more skilled workers before and after the use of these measures of technology. Nevertheless, my results continue to hold when I control for a plant's financial constraints and its workforce characteristics other than skills. These variables are often mentioned as unobserved or omitted factors that could be driving the cross-sectional correlations between technology use and skill upgrading in previous studies.

The next section describes the country's background, data, and presents descriptive and semiparametric evidence. Section 3 introduces a cost function approach to skill upgrading and discusses the estimation results. Section 4 addresses skill upgrading using a production function framework and discusses the estimation results. Section 5 concludes.

2. Country background, data and semiparametric evidence

2.1 Country background, data, and descriptive evidence

Chile presents an interesting setting to study the relationship between skill upgrading, new investment, and technology. As I show later, from 1979 to 1986 the share of skilled workers in total manufacturing employment increased by 16.8%. At the same time, the skill premium (measured as the ratio of average annual wage of skilled labor to average annual wage of unskilled labor) grew by 10.6%. These increases followed a trade liberalization. Between 1974 to 1979 Chile eliminated most of its non-tariff barriers and reduced tariff rates from more than 100% in 1974 to a uniform across industries 10% ad valorem tariff in 1979 (Dornbusch, et. al. (1994)). Its commitment to free trade persisted during the 1980s, except for a transitory period of increased tariff protection starting in 1983 in response to the 1982-1983 recession. These temporary measures peaked in 1984, when tariffs increased uniformly to 35%. However, Chile did not introduce non-tariff barriers, and tariffs declined to a 20% ad-valorem level in mid 1985 (UNCTAD, 1992). As a result of significant tariff reductions and elimination of non-

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Katz and Autor (1998) provide an overview of the labor studies, while Slaughter (1998) summarizes the work that tariff barriers to trade, the relative prices of imported technology decreased. The anecdotal evidence suggests that many firms benefited from the ability to upgrade their machinery and intermediate materials with purchases from abroad. Descriptive statistics presented at the end of this section based on the Census of Manufacturers' support the anecdotal evidence.

This paper draws on a census of Chilean manufacturing plants that employ ten or more workers. The data were collected by Chile's National Institute of Statistics from 1979 to 1986. The data contain observations on 4547 plants and a total of 26,513 plant-year observations. The unit of observation in the data is a plant, not a firm. Over 90% of the plants, however, are single-plant firms. The data set, the variable definitions, and the variable construction are described in detail in Liu (1993) and Tybout (1996).[4] Capital, investment, imported materials, value added, expenditures on patents and rights, and the expenditure on foreign technical assistance are expressed in constant 1980 pesos. The census distinguishes between production and nonproduction workers, and it additionally decomposes each of these two categories into white-collar and blue-collar workers. I measure skilled (white-collar) and unskilled (blue-collar) labor by the total number of employees in each skill group working in a plant. The data do not provide information on hours worked. For every plant, I obtain a wage for skilled (unskilled) workers by dividing the total wage bill for a given skill group by the number of employees in that skill group.

The data provide several plant-level variables to measure technology: imported materials, expenditures on patent use and rights, and expenditures on foreign technical assistance. I depict these variables in two ways. First, I create indicator variables for whether a plant receives foreign technical assistance, pays for patent use, or imports a portion of its materials. Second, I express foreign technical

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focuses on trade and product price related explanations.

[4] I use the records from 4547 plants after eliminating those with incomplete information. The capital variable was initially constructed using a perpetual inventory method by Liu (1993) and is described in detail in Tybout (1996). I have reconstructed the variable so that the capital stock at time t does not contain investment at time t. Since the balance sheet information was only available for the plants in 1980 and 1981, capital measures are based on the book value of capital in those two periods. In my capital variable, I use figures based on the 1981 book value of capital if

assistance cost as a share of value added, patent cost as a share of value added, and imported materials as a share of total materials. The second definition controls for disparities in the use of the technology measures across plants of different sizes. The findings in the paper are robust to both definitions of the variables. Of course, these technology measures are not ideal. Nevertheless, they provide more insight into the relationship between technology and skill upgrading than aggregate industry level data, since one can observe specific technology that is used by workers in a given plant. Table 1 reports descriptive statistics. Plants employ on average almost three times more unskilled than skilled workers, but the wages of skilled workers are more than double those of unskilled workers. Plants also differ significantly in their use of technology measures. Standard deviations are very high relative to the means of these variables.

Table 2 contains some descriptive statistics on employment and wages in Chilean manufacturing plants. The plants underwent some significant changes from 1979 to 1986. The average share of skilled workers in plant employment increased 16.8% and the average wagebill share of skilled workers grew 15%. At the same time, the skill premium (measured as the ratio of average annual wage of skilled workers to average annual wage of unskilled workers) grew by 10.6%. The concurrent rise in the skill premium and the relative employment of skilled workers is consistent with an upward shift in the relative demand for skilled workers during the early 1980s in Chile. Table 3 reports whether this shift occurred mostly within or between four digit ISIC industries.[5] As is standard in the literature, the change in the share of skilled workers in total employment (weighted by the share of industry employment in total employment) ΔS can be decomposed into within and between industry shifts:

$$\Delta S_t = S_t - S_\tau = \sum_i \Delta s_{it} E_{i.} + \sum_i \Delta E_{it} s_{i.}$$

both 1980 and 1981 are available. Otherwise, capital measure based on the 1980 book value of capital was used. I experimented with several options and all capital measures are highly correlated.

[5] Four-digit ISIC industry classification yields 84 industry categories.

where E_{it} is the share of industry i's employment in total employment at time t, s_{it} is the share of skilled workers in total employment in industry i, $E_{i.} = .5(E_{it} + E_{i\tau})$, and $s_{i.} = .5(s_{it} + s_{i\tau})$. The first and second term represent the shifts in the employment of skilled workers within and between industries, respectively. A similar decomposition can be obtained for the wagebill share of skilled workers. The decomposition results are reported in table 3. From 1979 to 1986 87% of the shift in the share of skilled workers in total manufacturing employment occurred within industries. Similarly, when the decomposition is based on the wagebill share of skilled workers, 64% of the shift occurred within industries. These within industry shifts are consistent with capital-deepening and skill-biased technological change. Have Chilean manufacturing plants invested more and used new technology? Table 4 summarizes the use of various technology measures and investment. Between 1979 and 1986 an increasing share of plants used foreign technical assistance, patents, and imported materials. The average expenditure on foreign technical assistance and the use of imported materials rose in real terms. The imported materials represented a growing proportion of total materials, and on average plants increased their investments.

2.2 Technology and the distribution of the employment of skilled workers across plants

Tables 2-4 provide suggestive evidence that Chile experienced skill upgrading at the same time as plants invested more heavily, and increased the use of imported materials, patented technology, and foreign technical assistance. That evidence relies on the means of these variables and might mask the differences in the impact of technology variables on plants that employ different shares of skilled workers. Recent industrial organization literature has revealed the importance of heterogeneity of plants within narrowly defined industry groups. To explore this heterogeneity, I examine the distribution of relative demand for skilled workers measured by the wagebill share of skilled workers across plants. I investigate whether technology measures impact plants in the entire distribution of plants by the same extent, or whether they exert bigger impact on plants in particular parts of the distribution. In order to do so, I compare the distribution of wagebill share of skilled workers in plants that use imported materials (or invest, receive foreign technical assistance, use patented technology) to the distribution of wagebill share of skilled workers in plants that do not.

Suppose that a vector of plant's characteristics x, its wagebill share of skilled workers s, and an indicator for whether a plant uses technology T have a joint distribution F(s, x, T). The density of relative demand for workers conditional on whether a plant uses a particular technology can be written as

(1) $$f_T(s) = \int_x dF(s, x \mid T = j) \equiv f(s \mid T = j)$$

where j is one if plant uses technology T and 0 otherwise. This density can be estimated with a kernel density function:

$$f_h = \frac{1}{n_j h} \sum_{i=1}^{n} K(\frac{s - s_i}{h}) 1(T = j)$$

where h is the bandwidth, *K()* is a kernel function, 1() is an indicator function whether a plant uses technology T, and n_j is the number of plants that use technology T ($n_j = \sum_{i=1}^{n} 1(T = j)$). Figure 1a shows the kernel density of the logarithm of the wagebill share of skilled workers for plants that do and do not use technology T. The indicator T is one if a plant invested, used imported materials, patented technology, and received foreign technical assistance at least one year from 1979 to 1986 and zero otherwise. The heterogeneity in the wagebill share of skilled labor across plants is striking. Moreover, the density for the plants that use these technology measures lies to the right of the density for plants that do not. This implies that the probability of observing a higher share of skilled workers (skill upgrading) is greater for plants that invest, use imported materials, foreign technical assistance, and patented technology. Figure 2 compares kernel densities for plants that do and do not use a particular technology in their production process. For example, the indicator T is one if a plant uses imported materials at least one year from 1979 to 1986 and zero otherwise(and similarly for other measures). The conclusions are the same. The mass of density for the plants that use imported materials, make new investments, use foreign technical assistance, or patents is to the right of the mass of density for the plants without the respective measure.

The above comparisons, however, ignore that plants that do or do not use technology might also differ in other characteristics. The difference in density of wagebill share of skilled workers might either be a result of the use of technology, or a result of the differing characteristics between the plants in the two groups. For example, if plants that use imported materials are also more capital intensive, and capital is complementary to skilled workers, I observe a difference in density of wagebill share of skilled workers regardless of the use of imported materials. In order to separate the two effects, I need to obtain the counterfactual distribution of the wagebill share of skilled workers for the plants that do not use imported materials that would have prevailed if these plants had the same other observable characteristics as the plants that use imported materials. If the difference between the counterfactual density of plants without technology and the actual density of plants with technology persists, then the technology measures seem to impact skill upgrading. Methodology proposed by DiNardo, et. al. (1996) enables such a counterfactual comparison. The basic idea behind the creation of the counterfactual density for the plants that do not use technology is to attach a greater importance (a larger weight) to plants without technology that better match the characteristics of the plants with technology.

Let $f_{x_1}(s|T=0)$ be the density of the wagebill share of skilled workers for plants that do not use technology T, but have the same characteristics x_1 as the plants that use technology T. Using (1), this yields:

$$\begin{aligned} f_{x_1}(s \mid T=0) &= \int_x f(s \mid x, T=0)\, dF(x \mid T=1) \\ &= \int f(s \mid x, T=0)\Psi_x(x)\, dF(x \mid T=0) \end{aligned}$$

where $\Psi_x(x) \equiv \dfrac{dF(x|T=1)}{dF(x|T=0)}$ is a reweighing function. Given an estimate of this reweighing function, I can obtain the estimate of counterfactual density by rewriting a kernel density function as:

$$f_t(s) = \frac{1}{n_t h} \sum_{i \in \Omega_t} \hat{\Psi}_x(x) K(\frac{s - s_i}{h}) 1(T = 0)$$

where n_t is the number of plants that do not use technology T. The reweighing function Ψ weighs the data by assigning a larger weight to plants that do not use technology T that better match the characteristics of the plants that use technology T. DiNardo, et. al. (1996) show that an estimate of the reweighing function can be obtained by applying Bayes rule to yield:

$$\begin{aligned} \Psi_x(x_i) &\equiv \frac{dF(x|T=1)}{dF(x|T=0)} \\ &= \frac{\Pr(T=1|x=x_i)}{\Pr(T=0|x=x_i)} \frac{\Pr(T=0)}{\Pr(T=1)}. \end{aligned}$$

Pr(T=1) is the unconditional probability that a plant uses technology T. I estimate $\Pr(T=1|x=x_i)$ by a Probit model with regressor vector x. I include the following plant characteristics as regressors: two-digit ISIC industry indicators, area indicators, indicators for capital quartiles, indicators for value added quartiles, and year indicators.

Figure 1b illustrates the counterfactual kernel density for the plants that do not use technology T and the actual densities from Figure 1a.[6] The counterfactual density lies between the actual density of the plants without technology T and the actual density of the plants using technology T. This suggests that part of the difference in the relative demand for skilled labor between the two types of plants stems from variation in other plant characteristics across the two groups. The mass of the actual density for plants that use technology measures is to the right of the counterfactual density even after controlling for other observable plant characteristics. The difference between the two densities measures the impact of investment and technology on skill upgrading. The impact is quite striking in the middle and upper part of the distribution, but technology does not exert much impact in the plants with relatively low share of skilled workers. Figure 3 depicts counterfactual densities for plants that do not use a particular technology measure and suggests similar findings as Figure 1b. The use of imported inputs and patented

[6] The technology indicator T is defined the same as for Figure 1a.

technology affects the whole distribution (except for the lowest tail). The effect of foreign technical assistance is very noticeable in the part of the distribution of plants with shares of skilled workers higher than .13 (ln(.13)=-2), but is negligible in plants that employ lower shares of skilled workers. The impact of new investment is pronounced mostly in plants in the middle section of the distribution, and diminishes for higher shares of skilled workers. Overall, these results show that various technology measures exert differential effect on skill upgrading over the distribution of plants.

This methodology has two drawbacks that should be considered when interpreting the results. First, it does not take into account the general equilibrium effects (or spillover effects) of the use of foreign technical assistance, patents on relative demand for skilled labor. For example, use of foreign technical assistance in a plant could increase demand for skilled labor in all plants if there exist spillovers. Second, the methodology assumes that conditional on the observed characteristics, the placement of imported materials (or investment, foreign technical assistance, patented technology) is random across plants. I do not account for unobservable plant characteristics that might impact placement of technology as well as skill upgrading. Plants that use imported materials could simply be plants with some unobserved characteristic that leads them to hire more skilled workers, or they might employ different type of workers than plants without imported materials. I address these concerns in the next two sections of the paper when I approach the topic more parametrically.

3. Cost Function Analysis

Previous section of the paper provided preliminary evidence on the positive relationship between increased relative demand for skilled labor and various technology measures across the distribution of plants. In this section, I address this topic parametrically by using a restricted variable translog cost function approach, which provides a way to relate plant characteristics to a plant's relative demand for skilled labor (skill upgrading).[7] The use of translog cost function is very appealing because it provides a

[7] This approach has been used widely in recent studies of skill upgrading (Berman, Bound, Griliches (1994), Feenstra and Hanson (1996, 1997), Doms et. al (1997), Machin and Van Reenen (1998) among others).

second order approximation to any cost function and it does not impose any restrictions on the substitutability of various inputs. In particular, I consider a restricted variable cost function form:

$$
\begin{aligned}
\ln C(w^s, w^u, Y, K, T) = {} & \alpha_0 + \alpha_s \ln w^s + \alpha_u \ln w^u + \alpha_y \ln Y + \alpha_k \ln K + \alpha_t T \\
& + .5\{\gamma_{su}(\ln w^s)(\ln w^u) + \gamma_{ss}(\ln w^s)^2 \\
& + \gamma_{us}(\ln w^u)(\ln w^s) + \gamma_{uu}(\ln w^u)^2\} \\
& + .5\left(\gamma_{yy}(\ln Y)^2 + \gamma_{kk}(\ln K)^2 + \gamma_{tt}T^2\right) + \gamma_{ys}(\ln Y)\ln(w^s) \\
& + \gamma_{yu}(\ln Y)(\ln w^u) + \gamma_{ks}(\ln K)(\ln w^s) + \gamma_{ku}(\ln K)(\ln w^u) \\
& + \gamma_{ts}T(\ln w^s) + \gamma_{tu}T(\ln w^u) + \gamma_{yt}(\ln Y)T + \gamma_{kt}(\ln K)T
\end{aligned} \tag{2}
$$

where C is a variable cost, w^s and w^u are wages of skilled and unskilled labor, respectively, Y is value added, K is capital, and T stands for technology. This framework differs from the general cost function specification because it assumes that capital and other technology measures T are fixed while skilled and unskilled labor are variable factors in the considered time period. Using cost minimization I obtain cost share equations of variable inputs by partially differentiating (2) with respect to input prices.

After imposing homogeneity of degree one in prices to ensure that the cost function corresponds to some well-behaved production function, the wagebill share equation for skilled labor can be written as:

$$
Share_s = \alpha + \gamma \frac{\ln(w^s)}{\ln(w^u)} + \gamma_k \frac{\ln(K)}{\ln(Y)} + \gamma_y \ln(Y) + \beta Tech + \varepsilon
$$

where the notation follows the previous notation in the paper. Technology term T is decomposed into directly observed technology measures vector *Tech,* and an unobserved component ε.

Estimation of the cost share equation relies on several assumptions. First, the previous literature assumes that capital and value added can be treated as variables not affected by the current wagebill share of skilled workers. In this paper, capital is constructed so that investment at time t does not enter capital until $t+1$. Therefore, not only can I assume that the share of current skilled workers does not affect the capital stock, but also capital is not affected by unobserved shocks that affect the wagebill share of skilled workers.[8] Moreover, value added is likely a function of the share of skilled workers employed in a plant. To mitigate this problem, I also estimate the cost share equation using lagged value added rather than the current value added.[9] The findings are robust and similar in both cases. Additionally, in section 4 of the paper I investigate skill upgrading based on a production function approach that does not rely on the assumption that value added is unaffected by the share of the skilled in the work force.

Second, I include area, four-digit ISIC industry, and time indicators in the regressions. These variables, for example, control for variation in the plant's wages based on area, industry, and time specific shocks to the labor market. As previous studies in the literature I do not include direct measures of plant level wages. The previous literature justifies the exclusion by the fact that most of the variation in relative wages across plants is endogenous (related to the different skill mixes of workers across plants).[10] Time and area indicators also control for other unobserved shocks that are common for all plants in a given year or area. The actual estimation equation for a plant i that belongs to industry j at time t therefore becomes:

$$(3) \qquad Share_{s,ijt} = \alpha + \gamma_k \frac{\ln(K_{it})}{\ln(Y_{it})} + \gamma_y \ln(Y_{it}) + \beta Tech_{it} + \delta Year_t + \phi Area_i + \lambda Ind_j + \varepsilon_{ijt}$$

where *Year* is a vector of year indicators, *Area* is an indicator that denotes the location of a plant, and *Ind* is a four-digit ISIC industry indicator. In part of the estimation, I also allow the coefficients on the capital to value added and value added to vary by industry. I do not impose constant returns to scale

[8] In this paper, I abstract from dynamic issues, in particular the issue of the exit of plants. Pavcnik (1999) shows that many plants exited in Chile during this time period. In unreported regressions that estimate the above relationship, I have included an indicator for plant exit. Conditional on other variables, the wagebill share of skilled workers is not statistically significantly higher or lower for the plants that exit. However, if the probability of exit depends on unobserved, skill biased shocks and is a function of a plant's capital, estimation based on surviving plants could lead to a downward bias on the coefficient of capital. Therefore it would make it more difficult to find capital-skilled labor complementarity.

[9] The regression results using current value added (tables 5, 6, 7) and lagged value added are similar. I therefore focus on the results using current value added. Results from regressions using lagged value added are reported in the appendix tables 3-6.

[10] This treatment of wages is a shortcoming of the cost based approach to skill upgrading. In section 4, I derive a reduced form for the relative plant-level employment of the skilled that does not suffer from this problem.

because value added enters in addition to the capital to value added ratio. If the coefficient on the value added variable γ_y is not significantly different from zero, I fail to reject the constant returns to scale hypothesis. If capital is complementary to skilled workers, the coefficient on the capital to value added ratio γ_k should be positive. If technology measures are skill biased, the components of the coefficient vector β should be positive.

Estimation results are reported in tables 5, 6, and 7. All regressions include four digit ISIC industry indicators so that the coefficients on the variables are identified by the variation in independent variables within industries.[11] All standard errors are adjusted for heteroskedasticity using Huber-White correction. I perform the analysis with two dependent variables--the wagebill share of skilled workers and the share of skilled workers in total plant employment. Because both yield similar results, I concentrate my discussion on the wage bill regressions. The results for the regressions using the share of skilled workers in total employment as dependent variable are reported in appendix tables 1 and 2. Table 5 reports regression results where technology variables are depicted as indicators for whether a plant receives foreign technical assistance, pays for use of patented technology, or imports a portion of its materials. Table 6 uses the alternative definition that is based on the expenditure on foreign technical assistance (or patents) as a share of value added and the share of imported materials in total plant materials. Since the results are similar in both cases, I focus my discussion on Table 5.

As column 1 shows, I find evidence of skill upgrading related to investment and technology measures. First, the coefficient on capital to value added ratio is positive and significantly different from zero in all cases. This indicates that capital is complementary to skilled labor: within an industry, holding other plant characteristics constant, plants that add additional capital also employ a higher share of skilled workers. Second, plants using foreign technical assistance, patented technology, and imported materials have a higher share of skilled workers in their wage bill: all the coefficients are positive and

[11] I have also performed the analysis for individual two digit ISIC industries separately (effectively allowing for a different cost function for all industries). The findings were essentially the same as in the pooled results discussed here.

significantly different from zero. Moreover, there is evidence of increasing returns to scale: the coefficient on value added is positive.

The estimation in table 7 allows the coefficients on the capital to value added ratio and value added to vary by industry. As column 1 indicates, plants in all industries display capital-skill complementarity and increasing returns to scale. Relative to food processing, capital-skill complementarity is stronger in paper, glass, basic metals, and machinery industries, but is not statistically different, for example, for plants in the textile industry. Allowing the coefficient on capital skill complementarity to vary across industries does not affect the previous findings of skill upgrading related to the use of foreign technical assistance, patented technology, and imported materials.[12]

Unlike in industry-level studies, the impact of skill upgrading in this paper is not identified by the differences in the use of imported materials, patented technology, or foreign technical assistance across industries. Rather, it is identified by the differences in the use of imported materials, patented technology, or foreign technical assistance between firms within an industry. Still, there are potentially two problems with interpretation of my findings. First, as most plant-level data studies, I do not have much information regarding the labor composition in each plant. Therefore, the coefficients on the variables such as foreign technical assistance, patents, and imported materials could simply capture that plants that use these measures employ a different mix of workers than those without them. Second, the variables representing skill biased technology could simply proxy for an omitted plant characteristic that affects relative demand for skilled labor and a plant's choice of technology use. For example, plants might differ in their ability to finance new investments, foreign technical assistance, patented technology, and imported materials. Their financial situation might also affect their ability to attract skilled workers.

To capture the effect of omitted plant characteristic, I estimate equation (3) first, using plant random effects, and second, using plant fixed effects.[13] Equations such as (3) are often estimated in difference form (first and long differences) in industry-level studies. Fixed effects estimation is in

[12] I have also allowed for industry specific coefficients on the latter variables, but the results were not informative.

principle analogous to differencing the data (exactly the same with two time periods).[14] It identifies the impact of the variable of interest solely with the intertemporal variation in the variable within a plant. It then eliminates the impact of any omitted time-invariant plant characteristics. Finding any correlation between variables of interest with this methodology is highly unlikely. First, fixed effects estimation exacerbates any measurement error problems and attenuates the coefficients on mismeasured variables toward zero. It is therefore much more reliable with better measured variables. Second, since it relies on within plant variation in a variable, it is more effective with a longer panel. Finally, most of the relevant variation in technology variables and the wagebill share of skilled labor might actually occur across rather than within plants in a given industry. My previous findings are robust to random effects estimation reported in column 2 of table 5. Not surprisingly, as column 3 of table 5 indicates, most of the coefficients become insignificantly different from zero in plant fixed effects estimation. Surprisingly, the fixed effects estimates confirm capital skill complementarity. Overall, since the capital-skill complementarity is based solely on the within plant variation, the above results suggests that plants that invested during the 1980s increased their relative demand for skilled labor over time.

It is impossible to identify whether the lack of correlation between skill upgrading and imported materials, patented technology, and foreign technical assistance is driven by the actual lack of relationship, the lack of within plant variation, or measurement error. The correlation between technology variables and skill upgrading disappears also in studies using plant level data from the United States sets (Doms et. al (1997)) if one relies only on within plant variation. Nevertheless, the lack of significant correlation between skill upgrading and technology measures using fixed effects might also suggest that only very particular plants decide to use imported materials, patented technology, or foreign technical assistance. These are also the plants that in general employ relatively more skilled workers before and after the adoption. These results suggest that future work should focus on trying to look

[13] The Hausman test rejects the hypothesis that the error is uncorrelated with the independent variables.
[14] I have estimated (3) in first and long differences, but the exercise did not yield different conclusions from those in the fixed effects estimation. Therefore, I focus on fixed effects results.

either at a longer time horizon or on finding instruments for the technology measures in order to solve the measurement error problem. The latter is notoriously difficult.

Given these caveats regarding fixed effects estimates, it might be attractive to consider alternative ways of controlling for "unobserved" plant characteristics such as workforce composition and financial situation. Chilean data decomposes skilled workers (white-collar) into administrators, executives, and production workers, and unskilled workers (blue-collar) into production and nonproduction workers. It also separates total plant employment by gender. In order to address the problem of plants employing different types of workers, I include regressors that provide more information on the composition of the workforce at the plant level. Column 4 of table 5 presents the results of a regression that controls for the share of skilled workers that are executives, the share of skilled workers that are administrators, the share of female employees in total plant employment, and the share of production workers in total plant employment. The magnitude of the coefficients on the technology variables decreases, but their impact on skill upgrading remains statistically significant. The coefficient on capital to output ratio is also reduced in magnitude, but remains highly significant.

Similarly, I can control for the problem that a plant's financial situation might impact its decisions to invest, import materials, use patented technology, or foreign technical assistance, as well as its ability to attract skilled workers. A plant's ownership structure might be a good indicator of its financial constraints. I control for a plant's financial situation by an indicator whether a plant is or belongs to a corporation. Columns 5 and 6 of table 5 report the coefficients from regressions that control for both worker characteristics and plant's ownership structure using OLS and random effects estimation, respectively. Except for patents, the previous findings are robust to the inclusion of these controls. As before, the inclusion of the corporation indicator diminishes the magnitude of all coefficients.

The finding of positive relationship between skill upgrading and imported materials and foreign technical assistance, after I account for various plant characteristics that were not controlled for in previous studies, has two implications. Since the magnitudes of the coefficients measuring the impact of various technology measures on skill upgrading decline, my results suggest that characteristics such as a plants' financial constraints do account for part of cross-sectional correlation between skill upgrading and technology use within an industry. They also provide several possible explanations for the differences in the adoption of technology across plants within an industry that should continue to be incorporated in future research.

4. Production function Analysis

The cost function approach assumes that plants face exogenous factor prices and choose factor quantities. In order to find links between plant level relative demand for skilled workers and plant level measures of technology, I specify a production function and assume that plants hire inputs to maximize profits. Suppose that output for plant i in industry j at time t can be written as:

(4)
$$Y_{ijt} = f\,(L_{ijt}{}^{s}, L_{ijt}{}^{u}, K_{ijt}, Tech_{ijt}; Z_{ijt})$$

where L^s and L^u are skilled and unskilled employment, K is capital, *Tech* is a vector with variables that indicate a plant's use of foreign technical assistance, imported materials, or patents, and Z is a vector of characteristics such as a year indicator, industry indicator, and the location of a plant. Let us assume that plants set workers' wages equal to their marginal revenue product of labor. This yields a factor demand for skilled labor (leaving out many subscripts)

$$w^s = \frac{\partial f}{\partial L^s} * p_j = f_s = f_s(K, L^u(w^u), L^s(w^s), Tech; Z) * p_j$$

and unskilled labor:

$$w^u = \frac{\partial f}{\partial L^u} * p_j = f_u(K, L^u(w^u), L^s(w^s), Tech; Z) * p_j$$

where $L^u(w^u)$ and $L^s(w^s)$ represent labor supply for unskilled and skilled workers, respectively and p_j is the price of product produced in industry j. By substituting in the relationship for the labor supply (for example, an alternative wage in an industry and a region) and rearranging the equation, I obtain a reduced form expression for the employment of the two skill groups:

$$L^s = f_s(K, altw^u, altw^s, Tech; Z) * p_j$$
$$L^u = f_u(K, altw^u, altw^s, Tech; Z) * p_j$$

where $altw^s$ and $altw^u$ are the alternative wage for skilled and unskilled workers, respectively. Log linearizing the relationship yields the following reduced form for the ratio of skilled to unskilled workers employed at a given plant:

$$\text{(5)} \qquad \ln(\frac{L^s}{L^u})_{ijt} = \gamma + \alpha_k \ln(K)_{ijt} + \alpha_u \ln(altw_{jt}{}^u) + \alpha_s \ln(altw_{jt}{}^s) + \beta Tech_{ijt} + \phi Z_{ijt} + \varepsilon_{ijt}$$

The coefficient on the capital α_k shows the impact of capital on the ratio of employment of the skilled to unskilled labor. If it is positive, it suggests that capital and skilled labor are complements. If the components of coefficient vector β on technology measures are not significantly different from zero, the evidence is consistent with foreign technical assistance, imported materials, and use of patented technology affecting productivity of skilled and unskilled workers symmetrically (Hicks neutral technology) or not impacting them at all. On the other hand, one could interpret a positive (negative) coefficient β as consistent with these measures representing technological progress that is relatively skill biased (unskilled biased).

Tables 8 and 9 report the regression results of estimating equation (5). All regression specifications control for four-digit ISIC industry, year, and area indicators.[15] All the results confirm my previous findings from the cost based approach. Capital is complementary to skilled labor in production in all specifications of the regression. The use of foreign technical assistance, patented technology, and imported materials is positively correlated with the relative employment of skilled workers. The coefficients are still positive and significant when I control for worker characteristics, plant ownership, and when I use plant random effects. As in the cost-function analysis, except for the capital-skilled labor

[15] All regressions also include plant size indicators (plants are divided into four quartiles based on the size of their labor force). I estimate (5) with and without inclusion of alternative wages. By construction (alternative wage is defined as the mean wage in an industry in a given area excluding the wage of a firm in question), these wages are highly correlated with the left hand side wage components from other firms and enter the equation significantly.

complementarity, my findings are not robust to the inclusion of plant fixed effects. Finally, table 10 reports the regression results of estimating (5) allowing for industry variation in the coefficient on capital. Positive relationship between skill upgrading and foreign technical assistance, patents, and imported materials continues to hold. Although all industries exhibit capital-skill complementarity, the complementarity is more pronounced in paper, chemicals, glass, basic metals, and machinery than food processing.

5. Conclusion

This paper finds that the use of imported materials, foreign technical assistance, and patented technology has contributed to skill upgrading in Chilean plants during the 1980s. Moreover, plants with more capital employ relatively more skilled workers. Since average plant investment increased in Chilean manufacturing plants during the 1980s, capital-deepening could additionally contribute to the growing relative demand for skilled workers. The relationship between skill upgrading and investment, the use of imported materials, and foreign technical assistance is likely to continue to be an important topic. During the 1990s, an increasing number of developing countries embarked on trade liberalization process and trade barriers between developed and developing countries declined after the Uruguay round of GATT negotiations. These trade developments might encourage more technology transfers that favor relatively skilled labor in less developed countries. Quantifying the impact of this additional technology transfers remains a topic for future research.

This paper complements the industry-level studies that cannot identify whether skill upgrading related to technology use occurs in all plants within an industry or whether it is driven by a specific set of firms. Semiparametric and parametric results suggest that plant heterogeneity is quite substantial. Like in previous plant level analysis by Doms et.al. (1997) for the United States, the results for technology measures other than capital are sensitive to the inclusion of plant fixed effects. The lack of significant coefficients might be due simply to the fact that the fixed effects methodology relies on intertemporal

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Their inclusion or exclusion does not affect the other coefficients in the regressions. I therefore only report the variation within plants. Yet, even if we found a positive link between skill upgrading and technology measures, this might not be a causal relationship, especially in the long run. A recent theoretical model by Acemoglu (1999) shows that increased demand for skilled labor can induce more skill biased technological change.

Given the inherent problems with fixed effects estimation, plant-level data enable me to control for part of the within industry plant heterogeneity by explicitly accounting for varying worker characteristics and financial constraints across plants within an industry. With these controls, the magnitude of the effects of technology variables on skill upgrading diminishes. However, the positive relationship between skill upgrading and imported materials and foreign technical assistance persists. This study thus illustrates that, to fully understand the process of technology adoption and how it relates to skill upgrading in less developed countries, future work should continue to explore plant characteristics such as financial constraints or managerial ability that affect a firm's ability to attract a better workforce and adopt better technology from abroad.

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regression results that include alternative wages as regressors.

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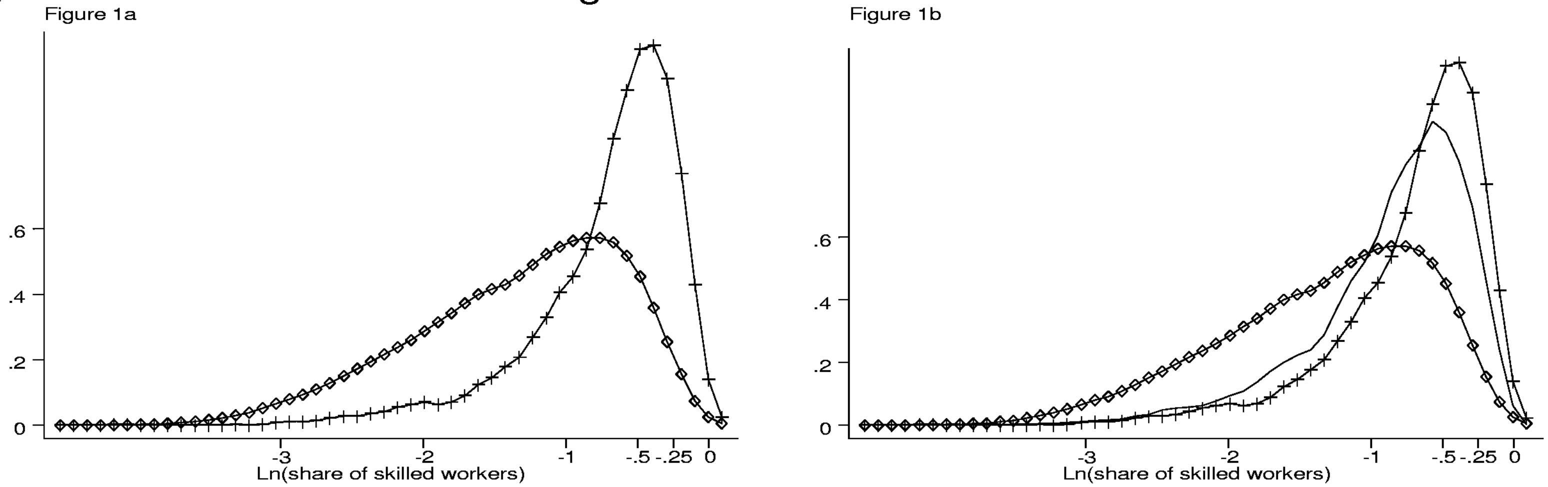
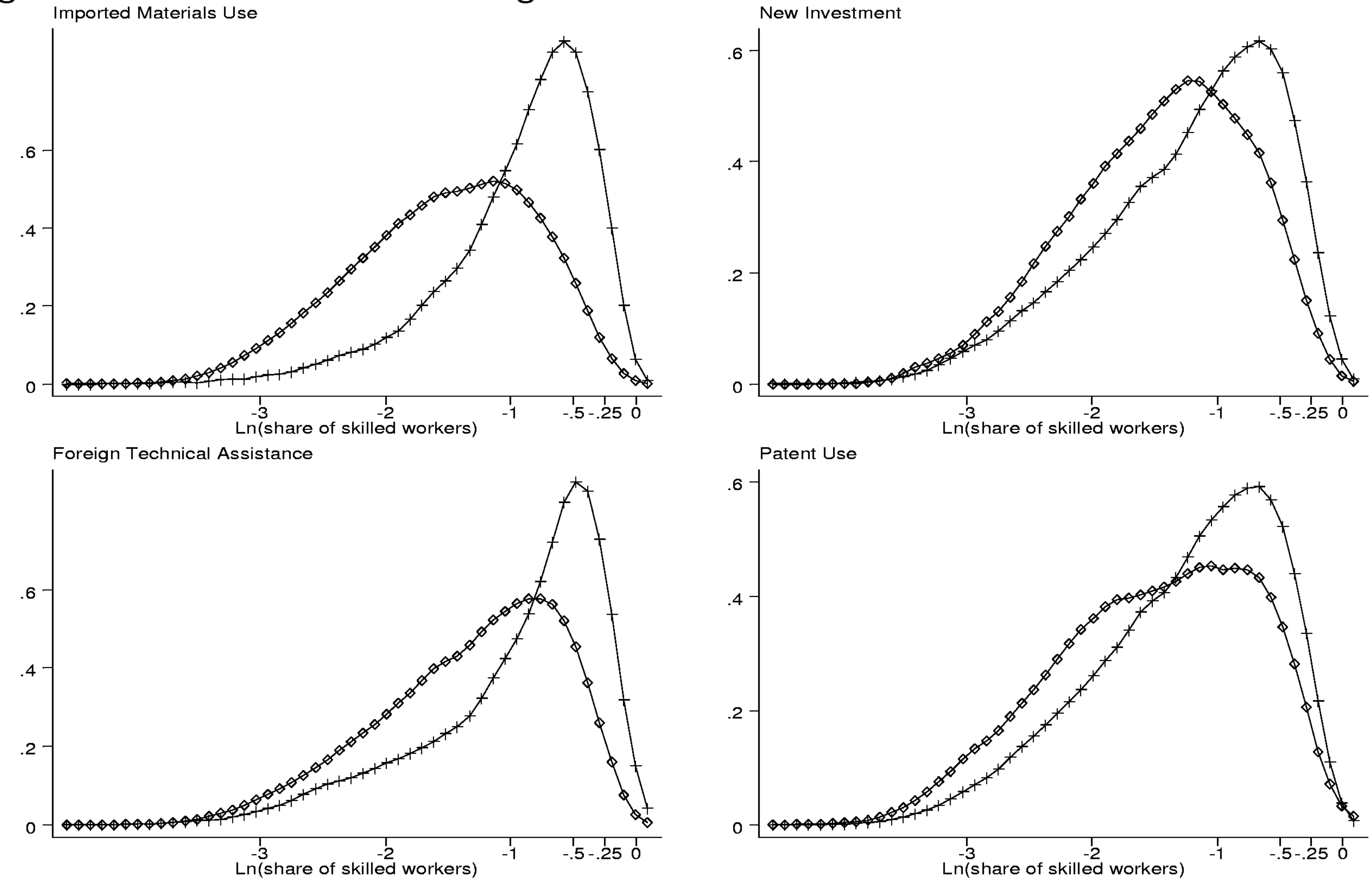
Figure 1--Kernel Densities of wagebill share of skilled workers



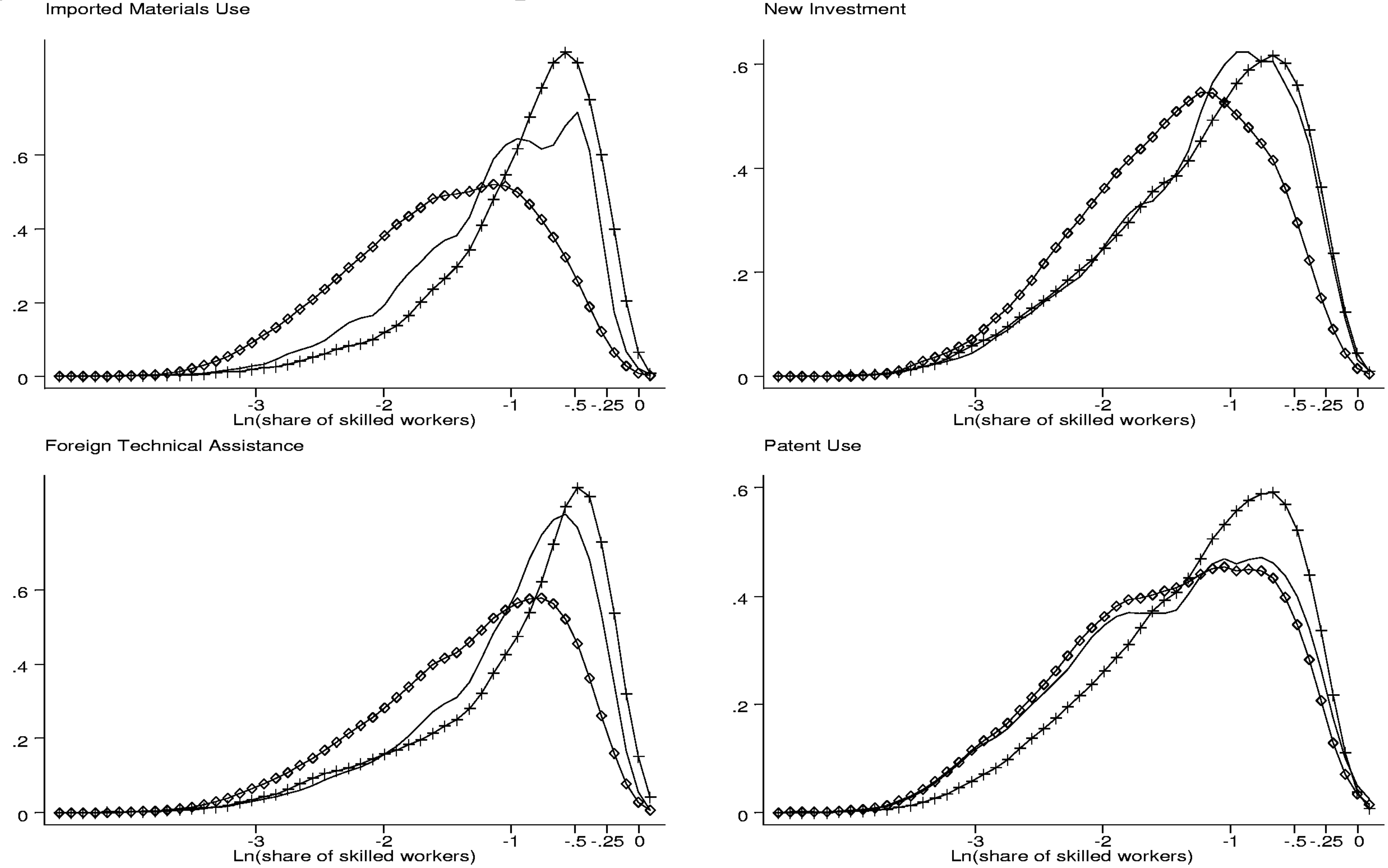
diamonds—plants without indicated technology; pluses—plants with indicated technology; solid line—reweighted density

Figure 2--Kernel densities of wagebill share of skilled workers



diamonds—plants without indicated technology; pluses—plants with indicated technology

Figure3-- Kernel densities of wagebill share of skilled workers



diamonds—plants without indicated technology; pluses—plants with indicated technology; solid line—reweighted density

Table 1
Descriptive Statistics

Variable	N	Mean	S.D.
Skilled Labor Wage	24,166	237	211
Unskilled Labor Wage	26,513	95	59
Skilled Workers	26,513	14	41
Unskilled Workers	26,513	41	86
Labor	26,513	56	120
Capital	26,513	54,429	356,870
Investment	26,513	3,872	41,026
Value Added	26,513	53,504	350,451
Foreign Technical Assistance (FTA)	26,513	295	3,647
Patent Use Cost	26,513	111	1,147
Imported Materials	26,513	16,771	223,482
Corporation Indicator	26,513	0.19	0.40
Executives	26,513	2	5
Administrators	26,513	8	24
Skilled Production Workers	26,513	4	21
Production Workers	26,513	39	81
Number of Women in a Plant	26,513	11	28

Note: Quantities in thousands of 1980 pesos. Skilled labor, unskilled labor and labor are measured in number of employees. The variable labor, but not the other two, also includes owners of a plant. There are only 24,166 observations on skilled wage because some plants do not employ any skilled workers. Source: Census of Manufacturers, Chilean National Instititue of Statistics.

Table 2
Skilled-Unskilled Labor Composition
(plant averages)

Year	Skill premium	Share of skilled labor in plant wage bill	Share of skilled labor in plant employment
	(1)	(2)	(3)
1979	2.62	.299	.184
1980	2.51	.293	.183
1981	2.49	.298	.185
1982	2.59	.330	.206
1983	2.73	.337	.208
1984	2.78	.340	.207
1985	2.71	.339	.208
1986	2.89	.345	.215
t-statistic	-2.310	-7.951	-8.247
p-value	.011	.000	.000

Note: The reported T-statistic is for the t-test of the equality of the mean in 1979 and 1986 for respective variables. The reported P value is for the alternative hypotesis Ha: 1986>1979. All quantities are in thousands of constant 1980 pesos. Labor variables are expressed in number of workers. Skill premium is the ratio of skilled wage to unskilled wage. Reported averages are simple (unweighted) means.

Table 3--Within and Between Industry Relative Labor Shifts 1979-1986

	Employment Share of Skilled Workers			Wage Bill Share of Skilled Workers		
	Total	Within	Between	Total	Within	Between
1979-86	.016	.015	.002	.053	.035	.018

Note: Definition of the decomposition is given on pages 8 and 9 of the paper. Decomposition is based on four digit ISIC industry classification. Employment share of skilled workers is weighted by the share of a four-digit ISIC industry employment in total employment in a given year. Wagebill share of skilled workers is weighted by the share of a four-digit ISIC industry wage bill in total wage bill in a given year.

Table 4--Technology Developments

Year	Plants that use foreign technical assistance (share)	Plants that Use Patents (share)	Plants with Imported Materials (share)	Foreign technical assistance cost (mean)	Patent Cost (mean)	Imported Materials (mean)	Imported Materials as a share of Total Materials (mean)	Investment (mean)
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
1979	.049	.724	.257	276	139	14,032	.081	3,161
1980	.045	.711	.238	290	59	13,766	.080	3,850
1981	.041	.756	.254	222	135	14,708	.086	3,896
1982	.043	.731	.231	241	118	14,580	.079	4,752
1983	.042	.780	.247	275	117	17,897	.087	3,757
1984	.052	.790	.265	370	103	21,137	.095	2,666
1985	.052	.812	.273	368	105	21,684	.093	3,481
1986	.057	.830	.289	362	114	18,977	.098	5,642
t-statistic	-1.448	-10.094	-2.836	-.773	.609	-.925	-3.188	-2.966
p-value	.074	.000	.002	.220	.729	.178	.001	.002

Note: Quantities are in thousands or 1980 Pesos. The reported T-statistic is for a test of the equality of the mean in 1979 and 1986 for respective variables. Reported P value is for the alternative hypothesis that Ha: 1986>1979.

Table 5--Skill upgrading Regressions
(dependent variable is share of skilled workers in wage bill)

	(1)	(2)	(3)	(4)	(5)	(6)
ln(capital/Value added)	.021 **	.027 **	.009 **	.014 **	.010 **	.016 **
	(.001)	(.001)	(.002)	(.001)	(.001)	(.001)
ln(Value added)	.046 **	.035 **	.007 **	.030 **	.021 **	.019 **
	(.001)	(.001)	(.002)	(.001)	(.001)	(.001)
FTA Indicator	.021 **	.009 **	-.003	.017 **	.007 *	.007 *
	(.005)	(.004)	(.005)	(.005)	(.004)	(.004)
Patent Indicator	.016 **	.005 **	.002	.005 **	.003	.000
	(.002)	(.002)	(.002)	(.002)	(.002)	(.002)
Imported Materials Indicator	.047 **	.014 **	-.003	.033 **	.023 **	.008 **
	(.003)	(.003)	(.003)	(.003)	(.003)	(.003)
Share of Executives				-.078 **	-.076 **	-.070 **
				(.005)	(.005)	(.004)
Share of Administrators				-.103 **	-.098 **	-.073 **
				(.004)	(.004)	(.003)
Share of Women				.018 **	.023 **	.007
				(.007)	(.007)	(.007)
Share of Production Workers				-.370 **	-.354 **	-.229 **
				(.008)	(.008)	(.006)
Corporation Indicator					.081 **	.082 **
					(.003)	(.004)
Plant Indicators	no	no	yes	no	no	no
Plant Randomn Effects	no	yes	no	no	no	yes
Industry Indicators	yes	yes	no	yes	yes	yes
Area Indicators	yes	yes	no	yes	yes	yes
Year Indicators	yes	yes	yes	yes	yes	yes
R^2 (adjusted)	.48	na	.80	.53	.54	na

Note: Huber-White standard errors are in parenthesis. ** and * indicate significance at a 5% and 10% level, respectively. FTA stands for foreign technical assistance. Share of executives and administrators refers to their share in total employment of skilled workers. Share of women and production workers refers to their share in total employment. N is 26,513. N is 24,166 in columns 3-5 because we cannot define additional variables such as share of executives and share of administators in total employment of skilled workers for plants without skilled workers. No findings change significantly in columns 1-3 if they are estimated using only 24,166 observations.

Table 6--Skill upgrading regressions
(dependent variable is share of skilled workers in wage bill)

	(1)	(2)	(3)	(4)	(5)	(6)
ln(capital/Value added)	.022 **	.027 **	.009 **	.015 **	.010 **	.016 **
	(.001)	(.001)	(.002)	(.001)	(.001)	(.001)
ln(Value added)	.049 **	.035 **	.007 **	.032 **	.021 **	.019 **
	(.001)	(.001)	(.002)	(.001)	(.001)	(.001)
FTA Cost/Value Added	.196 **	.051 *	-.004	.133 **	.094 *	.007
	(.063)	(.033)	(.028)	(.054)	(.046)	(.004)
Patent Cost/Value Added	.004 **	.002 **	.001 **	.002 **	.002 **	.000
	(.001)	(.001)	(.000)	(.001)	(.001)	(.002)
Imported Mat./Materials	.087 **	.034 **	-.001	.064 **	.049 **	.008 **
	(.007)	(.006)	(.007)	(.006)	(.006)	(.003)
Share of Executives				-.079 **	-.077 **	-.070 **
				(.005)	(.005)	(.004)
Share of Administrators				-.104 **	-.099 **	-.073 **
				(.004)	(.004)	(.003)
Share of Women				.018 **	.022 **	.007
				(.007)	(.007)	(.007)
Share of Production				-.372 **	-.354 **	-.229 **
Workers				(.008)	(.008)	(.006)
Corporation Indicator					.082 **	.082 **
					(.003)	(.004)
Plant Indicators	no	no	yes	no	no	no
Plant Randomn Effects	no	yes	no	no	no	yes
Industry Indicators	yes	yes	no	yes	yes	yes
Area Indicators	yes	yes	no	yes	yes	yes
Year Indicators	yes	yes	yes	yes	yes	yes
R^2 (adjusted)	.48	na	.80	.53	.54	na

Note: Huber-White standard errors are in parenthesis. ** and * indicate significance at a 5% and 10% level, respectively. FTA stands for foreign technical assistance. Share of executives and administrators refers to their share in total employment of skilled workers. Share of women and production workers refers to their share in total employment. N is 26,513. N is 24,166 in columns 3-5 because we cannot define additional variables such as share of executives and share of administators in total employment of skilled workers for plants without skilled workers. No findings change significantly in columns 1-3 if they are estimated using only 24,166 observations.

Table 7--Skill upgrading regressions with industry interactions
(dependent variable is share of skilled workers in wage bill)

	(1)	(2)	(3)
ln(capital/Value Added)	.017 **	.010 **	.014 **
	(.001)	(.001)	(.002)
ln(cap/Value Added)*textiles	.003	-.004 *	.000
	(.002)	(.002)	(.003)
ln(cap/Value Added)*wood	-.002	-.005 *	-.001
	(.003)	(.003)	(.003)
ln(cap/Value Added)*paper	.008 *	-.002	.003
	(.005)	(.004)	(.005)
ln(cap/Value Added)*chemicals	-.004	-.009 **	-.005
	(.003)	(.003)	(.003)
ln(cap/Value Added)*glass	.011 **	.003	.006
	(.005)	(.005)	(.005)
ln(cap/Value Added)*basic metals	.030 **	.022	.012 **
	(.005)	(.004)	(.005)
ln(cap/Value Added)*machinery	.013 **	.006 **	.006 **
	(.003)	(.002)	(.003)
ln(cap/Value Added)*other manuf.	.028 **	.011	.014
	(.007)	(.007)	(.009)
ln(Value Added)	.043 **	.020 **	.016 **
	(.002)	(.002)	(.002)
ln(Value Added)*textiles	.003	.001	.003
	(.002)	(.002)	(.003)
ln(Value Added)*wood	-.006 **	-.005 **	-.001
	(.003)	(.002)	(.003)
ln(Value Added)*paper	.016 **	.004	.010 **
	(.004)	(.003)	(.004)
ln(Value Added)*chemicals	.000	-.002	.003
	(.003)	(.003)	(.004)
ln(Value Added)*glass	.014 **	.008 **	.011 **
	(.004)	(.004)	(.005)
ln(Value Added)*basic metals	.008 *	.008 **	.011 **
	(.004)	(.004)	(.005)
ln(Value Added)*machinery	.012 **	.006 **	.005 *
	(.002)	(.002)	(.003)
ln(Value Added)*other manufacturing	.017 **	.006	.017
	(.007)	(.007)	(.010)

Note: This table continues on the next page

Table 7 continued--Skill upgrading regressions with industry interactions
(dependent variable is share of skilled workers in wage bill)

	(1)	(2)	(3)
list of coefficient continued			
FTA Indicator	.019 **	.006	.006
	(.005)	(.005)	(.004)
Patent Indicator	.016 **	.003	.000
	(.002)	(.002)	(.002)
Imported Material Indicator	.045 **	.022 **	.008 **
	(.003)	(.003)	(.003)
Plant Random Effects	no	no	yes
Industry Indicators	yes	yes	yes
Area Indicators	yes	yes	yes
Year Indicators	yes	yes	yes
R^2 (adjusted)	.49	.54	na

Note: Huber-White standard errors are in parenthesis. ** and * indicate significance at a 5% and 10% level, respectively. FTA stands for foreign technical assistance. Regressions in column 2 and 3 also include the following unreported regressors: share of executives and share of administrators in total employment of skilled workers, share of women and share of production workers in total employment, and a corporation indicator. N is 26,513 in columns 1 and 2, and 24,166 in column 3. N is 24,166 in column 3 because we cannot define additional variables such as share of executives and share of administators in total employment of skilled workers for plants without skilled workers. No findings change significantly in columns 1-2 if they are estimated using only 24,166 observations.

Table 8--Employment ratio regressions
(dependent variable is ln(skilled to unskilled labor))

	(1)	(2)	(3)	(4)	(5)	(6)
ln(capital)	.091 **	.086 **	.029 **	.063 **	.050 **	.054 **
	(.004)	(.005)	(.008)	(.003)	(.003)	(.004)
FTA Indicator	.187 **	.067 **	.012	.114 **	.086 **	.048 **
	(.021)	(.019)	(.022)	(.017)	(.017)	(.018)
Patent Indicator	.067 **	.025 **	.016	.025 **	.019 *	.008
	(.011)	(.009)	(.010)	(.010)	(.010)	(.008)
Imported Materials	.190 **	.052 **	-.011	.121 **	.091 **	.025 **
Indicator	(.012)	(.011)	(.013)	(.011)	(.011)	(.010)
Share of Executives				-.667 **	-.663 **	-.608 **
				(.023)	(.023)	(.018)
Share of Administrators				-.583 **	-.569 **	-.490 **
				(.020)	(.020)	(.015)
Share of Woman				.026	.041	.020
				(.029)	(.028)	(.030)
Share of Production				-2.137 **	-2.092 **	-1.604 **
Workers				(.040)	(.040)	(.026)
Corporation Indicator					.216	.232 **
					(.012)	(.018)
Plant Indicators	no	no	yes	no	no	yes
Plant Random Effects	no	yes	no	no	no	yes
Industry Indicators	yes	yes	no	yes	yes	yes
Area Indicators	yes	yes	no	yes	yes	yes
Year Indicators	yes	yes	yes	yes	yes	yes
R^2 (adjusted)	.31	na	.71	.46	.47	na

Note: Huber-White standard errors are in parenthesis. ** and * indicate significance at a 5% and 10% level, respectively. N is 24,166 because some firms do not report employing any skilled workers. FTA stands for foreign technical assistance. Share of executives and administrators refers to their share in total employment of skilled workers. Share of women and production workers refers to their share in total employment. The regression also includes the following unreported regressors: alternative wage for skilled workers, alternative wage for unskilled workers, plant size indicators based on the quartiles of the employment distribution. The coefficients are available from author upon request.

Table 9--Employment Ratio Regressions
(dependent variable is ln(skilled to unskilled labor))

	(1)	(2)	(3)	(4)	(5)	(6)
ln(capital)	.098 **	.087 **	.028 **	.066 **	.052 **	.055 **
	(.004)	(.005)	(.008)	(.003)	(.003)	(.004)
FTA Cost/Value Added	.680 **	.207	.086	.419 **	.335 **	.134
	(.260)	(.141)	(.138)	(.172)	(.153)	(.132)
Patent Cost/Value Added	.009	.000	-.001	-.001	-.001	-.006
	(.006)	(.005)	(.005)	(.009)	(.009)	(.004)
Imported Mat./Materials	.372 **	.108 **	-.029	.235 **	.186 **	.054 **
	(.027)	(.025)	(.027)	(.022)	(.022)	(.023)
Share of Executives				-.673 **	-.667 **	-.608 **
				(.024)	(.023)	(.018)
Share of Administrators				-.588 **	-.572 **	-.490 **
				(.020)	(.020)	(.015)
Share of Woman				.024	.040	.020
				(.029)	(.028)	(.030)
Share of Production Workers				-2.153 **	-2.100 **	-1.606 **
				(.040)	(.040)	(.026)
Corporation Indicator					.227 **	.236 **
					(.012)	(.018)
Plant Indicators	no	no	yes	no	no	yes
Plant Random Effects	no	yes	no	no	no	yes
Industry Indicators	yes	yes	no	yes	yes	yes
Area Indicators	yes	yes	no	yes	yes	yes
Year Indicators	yes	yes	yes	yes	yes	yes
R^2 (adjusted)	.31	na	.71	.46	.47	na

Note: Huber-White standard errors are in parenthesis. ** and * indicate significance at a 5% and 10% level, respectively. N is 24,166 because some firms do not report employing any skilled workers. FTA stands for foreign technical assistance. Share of executives and administrators refers to their share in total employment of skilled workers. Share of women and production workers refers to their share in total employment. The regression also inculdes the following unreported regressors: alternative wage for skilled workers, alternative wage for unskilled workers, plant size indicators based on the quartiles of the employment distribution. The coefficients are available from author upon request.

Table 10--Relative employment regressions with industry interactions
(dependent variable is ln(skilled to unskilled labor)

	(1)	(2)	(3)
ln(capital)	.072 **	.038 **	.041 **
	(.005)	(.005)	(.007)
ln(capital)*textiles	-.008	.005	.004
	(.008)	(.007)	(.011)
ln(capital)*wood	-.014	-.007	-.002
	(.010)	(.009)	(.013)
ln(capital)*paper	.072 **	.040 **	.037 **
	(.013)	(.011)	(.016)
ln(capital)*chemicals	.016 *	.000	.012
	(.009)	(.008)	(.013)
ln(capital)*glass	.067 **	.033 **	.035 *
	(.014)	(.012)	(.018)
ln(capital)*basic metals	.079 **	.061 **	.051 **
	(.015)	(.013)	(.019)
ln(capital)*machinery	.061 **	.043 **	.035 **
	(.009)	(.007)	(.011)
ln(capital)*other manufacturing	.029	.008	.048
	(.021)	(.017)	(.036)
FTA Indicator	.176 **	.083 **	.046 **
	(.021)	(.017)	(.018)
Patent Indicator	.066 **	.019 **	.008
	(.011)	(.010)	(.008)
Imported Materials Indicator	.181 **	.086 **	.024 **
	(.013)	(.011)	(.011)
Plant Random Effects	no	no	yes
Industry Indicators	yes	yes	yes
Area Indicators	yes	yes	yes
Year Indicators	yes	yes	yes
R^2 (adjusted)	.31	.47	na

Note: Huber-White standard errors are in parenthesis. ** and * indicate significance at a 5% and 10% level, respectively. N is 24,166 because some firms do not have any skilled workers. FTA stands for foreign technical assistance. All specifications also includes alternative wages and size distribution as regressors. Size indicators are based on quartiles in the distribution of employment. Regression in column 2 and 3 also included the following unreported regressors: share of executives and share of administrators in total employment of skilled workers, share of women and share of production workers in total employment, and corporation indicator. The coefficients are available from author upon request.

Appendix Table 1--Skill upgrading regressions
(dependent variable is employment share of skilled labor)

	(1)	(2)	(3)	(4)	(5)	(6)
ln(capital/Value added)	.010 **	.013 **	.004 **	.005 **	.003 **	.005 **
	(.001)	(.001)	(.001)	(.001)	(.001)	(.001)
ln(Value added)	.018 **	.014 **	.000	.004 **	.001 **	.003 **
	(.001)	(.001)	(.001)	(.001)	(.001)	(.001)
FTA Indicator	.026 **	.009 **	.001	.022 **	.019 **	.009 **
	(.004)	(.003)	(.003)	(.003)	(.003)	(.003)
Patent Indicator	.012 **	.005 **	.004 **	.002 *	.002	.001
	(.002)	(.001)	(.001)	(.001)	(.001)	(.001)
Imp. Materials Indicator	.025 **	.007 **	-.002	.014 **	.011 **	.003 *
	(.002)	(.002)	(.002)	(.002)	(.002)	(.002)
Share of Executives				-.098 **	-.097 **	-.092 **
				(.003)	(.003)	(.003)
Share of Administrators				-.087 **	-.085 **	-.074 **
				(.003)	(.003)	(.002)
Share of Women				-.001	.001	.000
				(.004)	(.004)	(.005)
Share of Production Workers				-.332 **	-.326 **	-.248 **
				(.006)	(.006)	(.004)
Corporation Indicator					.029	.032 **
					(.002)	(.003)
Plant Indicators	no	no	yes	no	no	no
Plant Randomn Effects	no	yes	no	no	no	yes
Industry Indicators	yes	yes	no	yes	yes	yes
Area Indicators	yes	yes	no	yes	yes	yes
Year Indicators	yes	yes	yes	yes	yes	yes
R^2 (adjusted)	.36	na	.75	.48	.48	na

Note: Huber-White standard errors are in parenthesis. ** and * indicate significance at a 5% and 10% level, respectively. FTA stands for foreign technical assistance. Share of executives and administrators refers to their share in total employment of skilled workers. Share of women and production workers refers to their share in total employment. N is 26,513. N is 24,166 in columns 3-5 because we cannot define additional variables such as share of executives and share of administators in total employment of skilled workers for plants without skilled workers. No findings change significantly in columns 1-3 if they are estimated using only 24,166 observations.

Appendix Table 2--Skill upgrading regression
(dependent variable is employment share of skilled labor)

	(1)	(2)	(3)	(4)	(5)	(6)
ln(capital/Value add.)	.011 **	.013 **	.004 **	.005 **	.003 **	.006 **
	(.001)	(.001)	(.001)	(.001)	(.001)	(.001)
ln(Value add.)	.020 **	.014 **	.000	.005 **	.002 **	.003 **
	(.001)	(.001)	(.001)	(.001)	(.001)	(.001)
FTA Cost/Value Ad.	.122 **	.032	.002	.073 **	.059 **	.016
	(.038)	(.022)	(.023)	(.031)	(.028)	(.020)
Patent Cost/Value Ad.	.002 *	.000	.000	.000	.000	-.001
	(.001)	(.001)	(.001)	(.002)	(.001)	(.001)
Imp. Mat./Materials	.057 **	.016 **	-.006	.039 **	.034 **	.007 **
	(.005)	(.004)	(.005)	(.004)	(.004)	(.003)
Share of Executives				-.098 **	-.098 **	-.092 **
				(.003)	(.003)	(.003)
Share of Administrators				-.088 **	-.086 **	-.075 **
				(.003)	(.003)	(.002)
Share of Women				-.001	.001	.000
				(.004)	(.004)	(.005)
Share of Production Workers				-.333 **	-.327 **	-.248 **
				(.006)	(.006)	(.004)
Corporation Indicator					.030 **	.033 **
					(.002)	(.003)
Plant Indicators	no	no	yes	no	no	no
Plant Randomn Effects	no	yes	no	no	no	yes
Industry Indicators	yes	yes	no	yes	yes	yes
Area Indicators	yes	yes	no	yes	yes	yes
Year Indicators	yes	yes	yes	yes	yes	yes
R^2 (adjusted)	.35	na	.75	.48	.48	na

Note: Huber-White standard errors are in parenthesis. ** and * indicate significance at a 5% and 10% level, respectively. FTA stands for foreign technical assistance. Share of executives and administrators refers to their share in total employment of skilled workers. Share of women and production workers refers to their share in total employment. N is 26,513. N is 24,166 in columns 3-5 because we cannot define additional variables such as share of executives and share of administators in total employment of skilled workers for plants without skilled workers. No findings change significantly in columns 1-3 if they are estimated using only 24,166 observations.

Appendix Table 3--Skill upgrading regressions with lagged value added
(dependent variable is share of skilled labor in wage bill)

	(1)	(2)	(3)	(4)	(5)	(6)
ln(capital/Lagged VA)	.021 **	.031 **	.008 **	.014 **	.009 **	.017 **
	(.001)	(.001)	(.003)	(.001)	(.001)	(.001)
ln(Lagged VA)	.047 **	.039 **	.008 **	.031 **	.022 **	.021 **
	(.001)	(.001)	(.003)	(.001)	(.001)	(.001)
FTA Indicator	.017 **	.009 *	-.003	.014 **	.005	.008 *
	(.005)	(.005)	(.006)	(.005)	(.005)	(.005)
Patent Indicator	.017 **	.006 **	.002	.006 **	.004	.001
	(.003)	(.002)	(.002)	(.003)	(.003)	(.002)
Imported Materials	.046 **	.013 **	-.004	.034 **	.024 **	.009 **
Indicator	(.003)	(.003)	(.003)	(.003)	(.003)	(.003)
Share of Executives				-.076 **	-.076 **	-.072 **
				(.005)	(.005)	(.005)
Share of Administrators				-.101 **	-.096 **	-.073 **
				(.004)	(.004)	(.004)
Share of Women				.018 **	.023 **	.010
				(.008)	(.007)	(.008)
Share of Production				-.370 **	-.356 **	-.237 **
Workers				(.009)	(.009)	(.007)
Corporation Indicator					.079 **	.082 **
					(.003)	(.005)
Plant Indicators	no	no	yes	no	no	no
Plant Randomn Effects	no	yes	no	no	no	yes
Industry Indicators	yes	yes	no	yes	yes	yes
Area Indicators	yes	yes	no	yes	yes	yes
Year Indicators	yes	yes	yes	yes	yes	yes
R^2 (adjusted)	.49	na	.81	.54	.55	na

Note: Huber-White standard errors are in parenthesis. ** and * indicate significance at a 5% and 10% level, respectively. FTA stands for foreign technical assistance. Share of executives and administrators refers to their share in total employment of skilled workers. Share of women and production workers refers to their share in total employment. N is 21,966. N is 20,166 in columns 3-5 because we cannot define additional variables such as share of executives and share of administators in total employment of skilled workers for plants without skilled workers. No findings change significantly in columns 1-3 if they are estimated using only 20,166 observations.

Appendix Table 4--Skill upgrading regressions with lagged value added
(dependent variable is share of skilled labor in wage bill)

	(1)	(2)	(3)	(4)	(5)	(6)
ln(capital/Lagged VA)	.022 **	.031 **	.008 **	.015 **	.009 **	.017 **
	(.001)	(.001)	(.003)	(.001)	(.001)	(.001)
ln(Lagged VA)	.050 **	.040 **	.008 **	.033 **	.022 **	.022 **
	(.001)	(.001)	(.003)	(.001)	(.001)	(.001)
FTA Cost/ LagVA.	.000	.000	.000	.000	-.001	.000
	(.001)	(.001)	(.000)	(.000)	(.000)	(.001)
Patent Cost/Lag VA	.019 *	.004	-.003	.016 **	.011 **	.002
	(.010)	(.006)	(.003)	(.006)	(.005)	(.006)
Imported. Mat./Materials	.092 **	.036 **	-.002	.069 **	.056 **	.026 **
	(.007)	(.006)	(.007)	(.006)	(.006)	(.006)
Share of Executives				-.078 **	-.076 **	-.072 **
				(.005)	(.005)	(.005)
Share of Administrators				-.102 **	-.097 **	-.073 **
				(.004)	(.004)	(.004)
Share of Women				.017 **	.022 **	.010
				(.008)	(.007)	(.008)
Share of Production Workers				-.372 **	-.356 **	-.237 **
				(.009)	(.009)	(.007)
Corporation Indicator					.081 **	.082 **
					(.003)	(.005)
Plant Indicators	no	no	yes	no	no	no
Plant Randomn Effects	no	yes	no	no	no	yes
Industry Indicators	yes	yes	no	yes	yes	yes
Area Indicators	yes	yes	no	yes	yes	yes
Year Indicators	yes	yes	yes	yes	yes	yes
R^2 (adjusted)	.49	na	.81	.54	.55	na

Note: Huber-White standard errors are in parenthesis. ** and * indicate significance at a 5% and 10% level, respectively. FTA stands for foreign technical assistance. Share of executives and administrators refers to their share in total employment of skilled workers. Share of women and production workers refers to their share in total employment. N is 21,966. N is 20,166 in columns 3-5 because we cannot define additional variables such as share of executives and share of administators in total employment of skilled workers for plants without skilled workers. No findings change significantly in columns 1-3 if they are estimated using only 20,166 observations.

Appendix Table 5--Skill upgrading regressions with lagged value added
(dependent variable is employment share of skilled labor)

	(1)	(2)	(3)	(4)	(5)	(6)
ln(capital/Lagged VA)	.010 **	.015 **	.004 **	.004 **	.002 **	.005 **
	(.001)	(.001)	(.002)	(.001)	(.001)	(.001)
ln(Lagged VA)	.019 **	.016 **	.001	.005 **	.001	.004 **
	(.001)	(.001)	(.002)	(.001)	(.001)	(.001)
FTA Indicator	.027 **	.009 **	-.001	.023 **	.020 **	.009 **
	(.004)	(.003)	(.004)	(.003)	(.003)	(.003)
Patent Indicator	.012 **	.005 **	.004 **	.002 **	.001	.001
	(.002)	(.001)	(.002)	(.002)	(.002)	(.001)
Imported Materials	.025 **	.007 **	-.003	.015 **	.011 **	.003 *
Indicator	(.002)	(.002)	(.002)	(.002)	(.002)	(.002)
Share of Executives				-.099 **	-.099 **	-.096 **
				(.004)	(.004)	(.003)
Share of Administrators				-.087 **	-.085 **	-.076 **
				(.003)	(.003)	(.002)
Share of Women				.000	.002	.004
				(.005)	(.005)	(.005)
Share of Production				-.336 **	-.331 **	-.259 **
Workers				(.007)	(.007)	(.004)
Corporation Indicator					.029 **	.032 **
					(.002)	(.003)
Plant Indicators	no	no	yes	no	no	no
Plant Randomn Effects	no	yes	no	no	no	yes
Industry Indicators	yes	yes	no	yes	yes	yes
Area Indicators	yes	yes	no	yes	yes	yes
Year Indicators	yes	yes	yes	yes	yes	yes
R^2 (adjusted)	.36	na	.76	.48	.49	na

Note: Huber-White standard errors are in parenthesis. ** and * indicate significance at a 5% and 10% level, respectively. FTA stands for foreign technical assistance. Share of executives and administrators refers to their share in total employment of skilled workers. Share of women and production workers refers to their share in total employment. N is 21,966. N is 20,166 in columns 3-5 because we cannot define additional variables such as share of executives and share of administators in total employment of skilled workers for plants without skilled workers. No findings change significantly in columns 1-3 if they are estimated using only 20,166 observations.

Appendix Table 6--Skill upgrading regressions with lagged value added
(dependent variable is employment share of skilled labor)

	(1)	(2)	(3)	(4)	(5)	(6)
ln(capital/Lagged VA)	.011 **	.015 **	.004 **	.005 **	.002 **	.005 **
	(.001)	(.001)	(.002)	(.001)	(.001)	(.001)
ln(Lagged VA)	.021 **	.017 **	.001	.006 **	.002 **	.004 **
	(.001)	(.001)	(.002)	(.001)	(.001)	(.001)
FTA Cost/ LagVA.	.000	.000	.000	-.001 **	-.001 **	.000
	(.000)	(.001)	(.000)	(.000)	(.000)	(.001)
Patent Cost/Lag VA	.013 **	.004	.001	.010 **	.008 **	.002
	(.006)	(.004)	(.003)	(.003)	(.003)	(.004)
Imp. Mat./Materials	.058 **	.014 **	-.011 *	.040 **	.035 **	.006 *
	(.005)	(.004)	(.005)	(.004)	(.004)	(.004)
Share of Executives				-.100 **	-.100 **	-.096 **
				(.004)	(.004)	(.003)
Share of Administrators				-.087 **	-.086 **	-.076 **
				(.003)	(.003)	(.002)
Share of Women				.000	.002	.004
				(.005)	(.005)	(.005)
Share of Production Workers				-.337 **	-.331 **	-.259 **
				(.007)	(.007)	(.004)
Corporation Indicator					.030 **	.032 **
					(.002)	(.003)
Plant Indicators	yes	no	yes	no	no	no
Plant Randomn Effects	no	yes	no	no	no	yes
Industry Indicators	yes	yes	no	yes	yes	yes
Area Indicators	yes	yes	no	yes	yes	yes
Year Indicators	yes	yes	yes	yes	yes	yes
R^2 (adjusted)	.35	na	.76	.48	.49	na

Note: Huber-White standard errors are in parenthesis. ** and * indicate significance at a 5% and 10% level, respectively. FTA stands for foreign technical assistance. Share of executives and administrators refers to their share in total employment of skilled workers. Share of women and production workers refers to their share in total employment. N is 21,966. N is 20,166 in columns 3-5 because we cannot define additional variables such as share of executives and share of administators in total employment of skilled workers for plants without skilled workers. No findings change significantly in columns 1-3 if they are estimated using only 20,166 observations.