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 in Chilean plants. 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 that some of the increased relative demand for skilled workers can be attributed to capital deepening. However, the relationship between skill upgrading and the three technology measures disappears once I control for unobserved plant characteristics. These results suggest that plant adoption of foreign technology is not associated with plant skill upgrading.

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1. Introduction

Growing demand for skilled workers and increased income inequality based on workers' skills present a severe problem for societies in developing countries: they precipitate the negative social consequences associated with higher initial poverty levels and income disparities. This paper investigates the relationship between growing demand for skilled labor (i.e. skill upgrading), investment, imported materials, and technology adoption using plant level data in Chile.

The 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 (Hanson an Harrison (1995, 1999, 1999a), Revenga (1997), Robbins (1995, 1996)). Second, most of the worker reallocation occurred within rather than across industries (Hanson an Harrison (1995), Robbins (1995, 1996)). Moreover, the share of skilled labor in total industry employment increased concurrently with an increase in the skill premium (Hanson and Harrison (1995), Robbins (1995, 1996)). These patterns cannot be explained solely by the strengthening of product-level import competition from developed countries after trade liberalizations.[1] However, they are consistent with the increase in demand for skilled labor due to the adoption of skill-biased technology. Although these labor market changes have been well documented, only Feenstra and Hanson (1997) and Hanson and Harrison (1999) analyze the sources of increased within industry demand for skilled workers in a less developed country and reach mixed conclusions.

[1] Increased exposure to trade from relatively skilled-labor abundant 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, tariff reductions should increase 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 the employment share of skilled workers.

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 rely on industry or individual worker level data. These studies find 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 is driven only by certain plants.[2] Moreover, a study of U.S. plants by Doms, Dunne, and Troske (1997) finds no association between the adoption of new technology and skill upgrading after controlling for unobserved plant characteristics. My plant level data presents a good setting to investigate the sources of skill upgrading while accounting for plant heterogeneity in the case of Chile.

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 closer. I therefore explore this demand shift further using plant-level data.

I first employ the methodology used in previous literature and consider skill upgrading by deriving a plant's demand for skilled labor in the context of a cost function. 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. A difficulty with the interpretation of

[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 Jensen (1999), Machin and Van Reenen (1998)), the use of computers at work (Berman, Bound, and Griliches (1994), Autor, Katz, and Krueger (1998)), exporting (Bernard

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 address this concern by exploiting the panel dimension of the data and controlling for unobserved time-invariant plant characteristics by using plant fixed effects or differencing the data. Moreover, the impact of technology on skill upgrading might differ for plants in various parts of plant distribution. I analyze these differences and 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, Fortin, and Lemieux (1996). Working with the entire distribution of the share of skilled workers in plants allows me, for example, to observe where in the distribution of plants new investment and technology exert the biggest influence.

I find that the increase in investment by Chilean manufacturing plants could partially explain the growing demand for skilled labor in Chile during the 1980s. However, the increased demand for skilled labor cannot be attributed to the plant adoption of foreign technology. My analysis suggests that only certain plants acquire technology through patents, imported materials, or the use of foreign technical assistance and these plants employ relatively more skilled workers before and after the technology adoption. Semiparametric analysis of the relationship between technology measures and skill upgrading over the entire plant distribution of the share of skilled workers additionally shows that the main differences in skilled labor use between plants that use foreign technology and those that do not arises in very skill intensive plants.

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

2. Data and Country Background

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and Jensen (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.

I explore the relationship between skill upgrading and technology adoption using the census of Chilean manufacturing plants that employ ten or more workers collected by Chile's National Institute of Statistics from 1979 to 1986. The data set, the variable definitions, and the variable construction are described in detail in Liu (1993) and Tybout (1996). The data is an unbalanced panel of 4547 plants and a total of 26,513 plant-year observations.[3] The unit of observation in the data is a plant, not a firm. Over 90% of the plants, however, are single-plant firms. Capital, investment, imported materials, value added, expenditures on patents and rights, and the expenditures on foreign technical assistance are expressed in 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 include 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 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

[3] 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

can observe specific technology that is used by workers in a given plant. Table 1 reports descriptive statistics.

Chile presents an interesting setting to study the relationship between skill upgrading, investment, and technology adoption in developing countries. Preliminary analysis suggests that the plants experienced an increased demand for skilled workers at the same time they increased their investment and adopted new technology from 1979 to 1986. To begin with, table 2 contains the descriptive statistics on employment and wages in Chilean manufacturing plants. 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. Second, most of this shift occurred within four digit ISIC industries. Table 3 decomposes the change in the share of skilled workers in total employment (weighted by the share of industry employment in total employment) from 1979 to 1986 ΔS into within and between industry shifts, respectively: $\Delta S_t = S_t - S_\tau = \sum_i \Delta s_{it} E_{i.} + \sum_i \Delta E_{it} s_{i.}$, 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 decomposition suggests that 89% of the shift in the share of skilled workers in total manufacturing employment occurred within industries. A similar decomposition for the wagebill share of skilled workers reported in the right panel of the table confirms these results. The within industry shifts are consistent with skill upgrading related to capital-deepening and adoption of skill-biased technology.

Third, skill upgrading occurred at the same time as plants invested more heavily and increased the use of foreign technology. Table 4 summarizes the use of technology measures and investment from

capital if 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.

1979 and 1986 and indicates that 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. Thus, 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 Chile. In sum, the descriptive evidence suggests that the skill upgrading could *in principle* be attributed to increased use of foreign technology and capital deepening.

Note that capital deepening and adoption of foreign technology by Chilean plants could have in part be associated with the 1974-1979 trade liberalization that eliminated most of the non-tariff barriers (NTBs) and reduced tariff rates from more than 100% in 1974 to a uniform across industries 10% ad valorem tariff in 1979 (Dornbusch and Edwards (1994)). The reductions in trade barriers drastically lowered the relative prices of imported machinery and technology and enabled many firms to upgrade their machinery and intermediate materials with purchases from abroad (Edwards and Edwards (1987)). The observed plant responses are in line with recent studies by Eaton and Kortum (1996, 1997) that 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. Moreover, the increased plant investment and the use of foreign technology is also consistent with Pavcnik (2002) that finds increased productivity of Chilean plants in sectors that faced more foreign competition after trade liberalization and with what Wood (1995) has labeled “defensive innovation”: firms in sectors facing intensified import competition look for new methods of production that economize on costs.

3. Cost Function Analysis

I formally investigate the relationship between skill upgrading, firm investment, and the use of foreign technology using a restricted variable translog cost function approach.[4] I assume that the capital is a quasi-fixed factor and that plants minimize the cost of skilled and unskilled labor. This cost minimization yields the expression for the share of skilled labor in total wagebill of a plant (i.e. relative demand for skilled labor):

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

where $Share_s$ represents the share of skilled labor in total wagebill of a plant, w^s and w^u are wages of skilled and unskilled labor, respectively, Y is value added, K is capital, and technology term is decomposed into directly observed technology measures vector *Tech,* and an unobserved component ε.

Before presenting the empirical results, let me highlight some particular features of the estimation. First, capital and value added are treated as variables not affected by the current wagebill share of skilled workers. Since investment at time *t* does not enter capital until *t+1* in the data, capital is not affected by unobserved shocks that affect the wagebill share of skilled workers.[5] 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. The findings are similar in both cases, so I focus on the results based on current value added.[6] Second, I control for the unobserved shocks to the relative demand for skilled workers common to an area, industry, or time by include area, four-digit ISIC industry, and time indicators in the regressions. Third, as

[4] This approach has been used widely in recent studies of skill upgrading in developed countries (see Berman, Bound, and Griliches (1994), Doms et. al (1997), Machin and Van Reenen (1998)). The translog cost function is very appealing because it provides a second order approximation to any cost function and it does not impose any restrictions on the substitutability of various inputs.

[5] I abstract from dynamic issues, in particular the issue of the exit of plants. Pavcnik (2002) shows that many plants exited in Chile during this time period. Some unreported regressions that explicitly control for plant exit suggest that, 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.

[6] Additionally, in an older version 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 labor in plant employment. No conclusions change. All these results are available from the author upon request.

previous literature I do not include direct measures of plant level wages because most of the variation in relative wages across plants is endogenous (i.e. related to the different skill mixes of workers across plants).[7] The actual estimation equation for a plant i that belongs to industry j at time t therefore becomes:

$$Share_{s,ijt} = \alpha + \gamma_k \frac{\ln(K_{it})}{\ln(Y_{it})} + \gamma_y \ln(Y_{it}) + \beta Tech_{it} + \delta Year_t + \phi Area_i + \lambda Ind_j + \varepsilon_{ijt} \qquad (1)$$

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. 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 table 5.[8] In columns 1-3, I depict technology variables with indicators for whether a plant receives foreign technical assistance, pays for use of patented technology, or imports a portion of its materials. In columns 4-6, I use the alternative definition for technology variables 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 both yield similar results, I focus my discussion on columns 1-3. All standard errors are adjusted for heteroskedasticity using Huber-White correction.

In order to compare my findings with previous literature, I first explore the relationship between skill upgrading and technology use by relying on the variation *across plants within an industry*. Column 1 of table 5 suggests that investment and the adoption of technology is associated with a higher use of more skilled workers. First, the coefficient on capital to value added ratio is positive and significantly different from zero. This indicates that capital might be complementary to skilled labor: within an

[7] This treatment of wages is a shortcoming of the cost based approach to skill upgrading. As a specification check, I also estimated a reduced form for the relative plant-level employment of the skilled workers based on a production function that does not suffer from this problem. This approach yielded the same conclusions.

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 significantly different from zero.[9] Some of my findings are in line with previous work by Hanson and Harrison (1999), who explore the impact of foreign direct investment (FDI) and adoption of new technology, investment, and imported materials on skill upgrading using plant level data from Mexico. Relying on the variation *across plants within an industry*, they find that firms that receive FDI, acquire technology through licensing agreements, or firms that import materials hire more skilled workers. However, they obtain a negative or insignificant relationship for other measures of investment and technology change.

Yet, identifying the relationship between technology adoption and skill upgrading based on the variation *across* plants within an industry is problematic. The technology variables could be correlated with an omitted plant characteristic (for example, managerial ability or financial constraints) that affects the relative demand for skilled labor independent of technology use. This would bias the results. If these unobserved plant characteristics are time-invariant, one can control for unobserved plant heterogeneity with plant fixed effects. Plant fixed effects estimation is in principle analogous to differencing the data (exactly the same with two time periods) since it identifies the impact of the variable of interest solely with the intertemporal variation in the variable within a plant. The fixed effects estimates are reported in column 2 of table 5. I continue to find positive association between additional plant investment and skill

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[8] All regressions were redone using the share of skilled workers in total plant employment as a dependent variable and yielded similar findings. The regressions are available from the author upon request.

[9] The relationship between skill upgrading and independent variables in equation (1) could differ across industries. The estimation in appendix table A.1 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 (the base group), 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. I have also allowed for industry specific coefficients on the latter variables, but the results were not informative.

upgrading. However, the estimates of the coefficients on technology variables become statistically insignificant.[10]

It is difficult to identify whether the lack of correlation between skill upgrading and the use of imported materials, patented technology, and foreign technical assistance is driven by the actual lack of relationship or measurement error in technology variables that would attenuate the estimated coefficients. Measurement error concerns might be partially alleviated by relying on longer differences of the data. I thus estimate a specification of equation (1), where all variables are expressed as 5-year differences (column 3). The results confirm that additional investment is associated with skill upgrading. However, as in the plant fixed effects estimation, the coefficients on other technology variables are not statistically different from zero. Estimates of equation (1) in 6-year differences also yield similar conclusions. Thus, adoption of foreign technology does not seem to be associated with increased demand for skilled labor in the case of Chile even in specifications that are less likely to suffer from attenuation bias.

In sum, we find no support that adoption of foreign technology is associated with the increased demand for skilled labor. While the Chilean plants adopted foreign technology after the large trade liberalization, these technology changes were not associated with increases in demand for skilled labor. Plants that adopted technology were more skill intensive prior to adoption of technology and I find no evidence that these plants became relatively more skill intensive over time. This result might be at first surprising given that many industry level studies find a positive relationship between various technology measures and skill upgrading. However, these studies do not account for unobserved heterogeneity across plants within an industry. The lack of significant correlation between skill upgrading and technology measures using within plant variation might 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 of technology. In this respect, my results confirm the findings by Doms et.al. (1997) for the U.S. plants.

[10]The estimation that allows the coefficients on the capital to value added ratio and value added to vary by industry yields similar findings (see column 2, appendix table A.1).

4. Semiparametric Evidence

The evidence on skill upgrading and technology adoption presented in previous section 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 next examine the distribution of 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 particular, 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

$$f_T(s) = \int_x dF(s, x \mid T = j) \equiv f(s \mid T = j) \qquad (2)$$

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

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

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 construct 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 (2), 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:

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

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.[11] Two noteworthy results emerge. First, the counterfactual density lies between the actual density of the plants without technology T and the actual density of the

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

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. Second, 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 effect is quite striking in the middle and upper part of the distribution, but technology does not exert much influence on skill upgrading in the plants with relatively low share of skilled workers. Figure 2 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 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 exceeding .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.

Since the above methodology assumes that conditional on the observed characteristics, the placement of new technology is random across plants, one should be cautious about the causal interpretation of the results. Nevertheless, the evidence insinuates that, even after accounting for differences in observable characteristics across plants, the relationship between various technology measures and skill upgrading differs substantially over the distribution of plants. While the impact of technology use on the share of skilled labor is negligible for the plants in the lower tail of the distribution of the share of skilled labor, it becomes more pronounced in the middle and upper tail of the distribution. This suggests that the main differences in skilled labor use between plants that use foreign technology and those that do not arise for very skill intensive plants.

5. Conclusion

This paper explores the sources of the growing demand for skilled labor in Chile following the drastic trade liberalization during the 1980s. This trade liberalization reduced the relative price of imported machinery, materials, and technology and significantly exposed domestic producers to foreign competition. These developments were associated with increases in plant investment and in the use of foreign technology, which *a priori* hinted that the skill upgrading could be attributed to capital deepening and increased use of foreign technology. My results suggest that an increase in plant investment leads to an increase in the relative demand for skilled labor. Since average plant investment increased in Chilean manufacturing plants during the 1980s, capital deepening provides a possible explanation for the growing relative demand for skilled workers. However, I find that the use of imported materials, foreign technical assistance, and patented technology is *not* associated with the increased demand for skilled workers in Chilean plants during the 1980s.

These results might be at first surprising given that many industry level studies find a positive relationship between skill upgrading and various technology measures. However, my analysis suggests that it is crucial to account for unobserved plant characteristics that affect plant technology adoption and independently influence the demand for skilled labor. Doms et. al. (1997) reach similar conclusions in their study of U.S. plants. Overall, the importance of plant heterogeneity within an industry suggests 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 adopt better technology and attract a more skilled workforce.

My analysis has several shortcomings. To begin with, because the Chilean data does not provide the information on FDI, I am not able to explore the relationship between FDI and skill upgrading. Yet, FDI provides an important channel for technology transfers from developed to developing economies. For example, Feenstra and Hanson (1997) and Hanson and Harrison (1999) find positive association between FDI and skill upgrading in Mexico. FDI could potentially contribute to increased demand for skilled labor in Chile. Second, this study explores plant technology adoption and skill upgrading over the period of 8 years. My results are robust across specifications that identify the relationship between skill upgrading and technology adoption with short and long differences of the variables. Nevertheless, the lack of relationship between skill upgrading and technology adoption could be driven by the specific period of the study or could be due to the relatively short period of time I can follow the firms. Thus, estimation of the relationship between skill upgrading and technology adoption over a longer period of time would provide a useful future extension.

Finally, the relationship between skill upgrading and 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 WTO negotiations. These trade developments might encourage more technology transfers that favor relatively skilled labor as the relative price of imported technology decreases and firms are pressured to improve their productivity when faced by increased foreign competition. Quantifying the impact of these technology transfers on demand for skilled labor remains a topic for future research.

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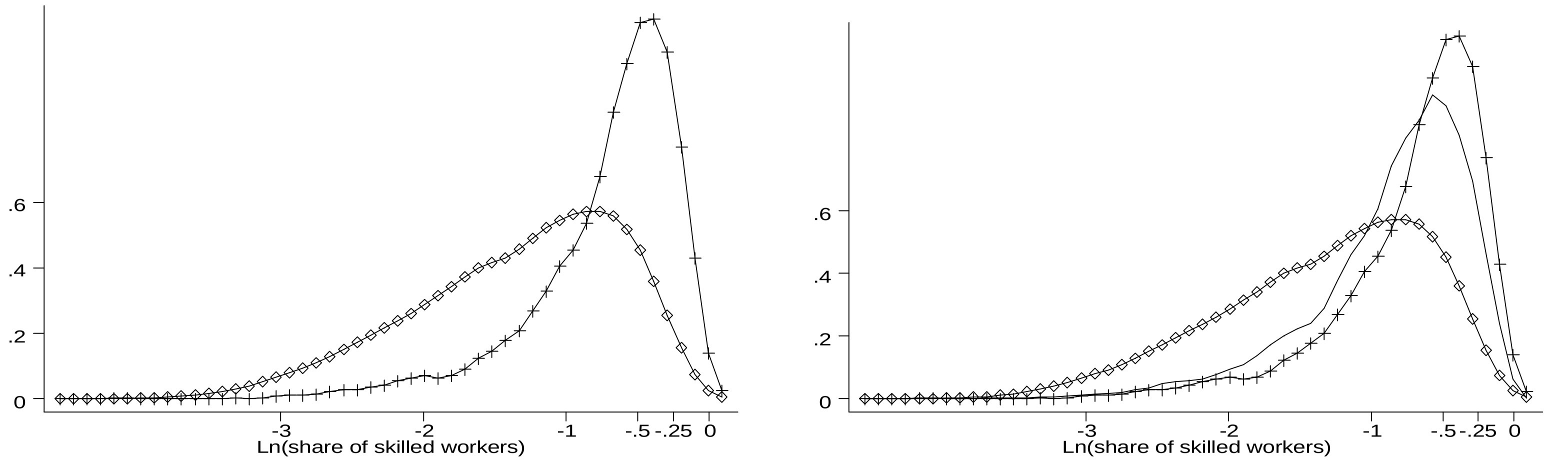
Figure 1--Kernel Densities of wagebill share of skilled workers

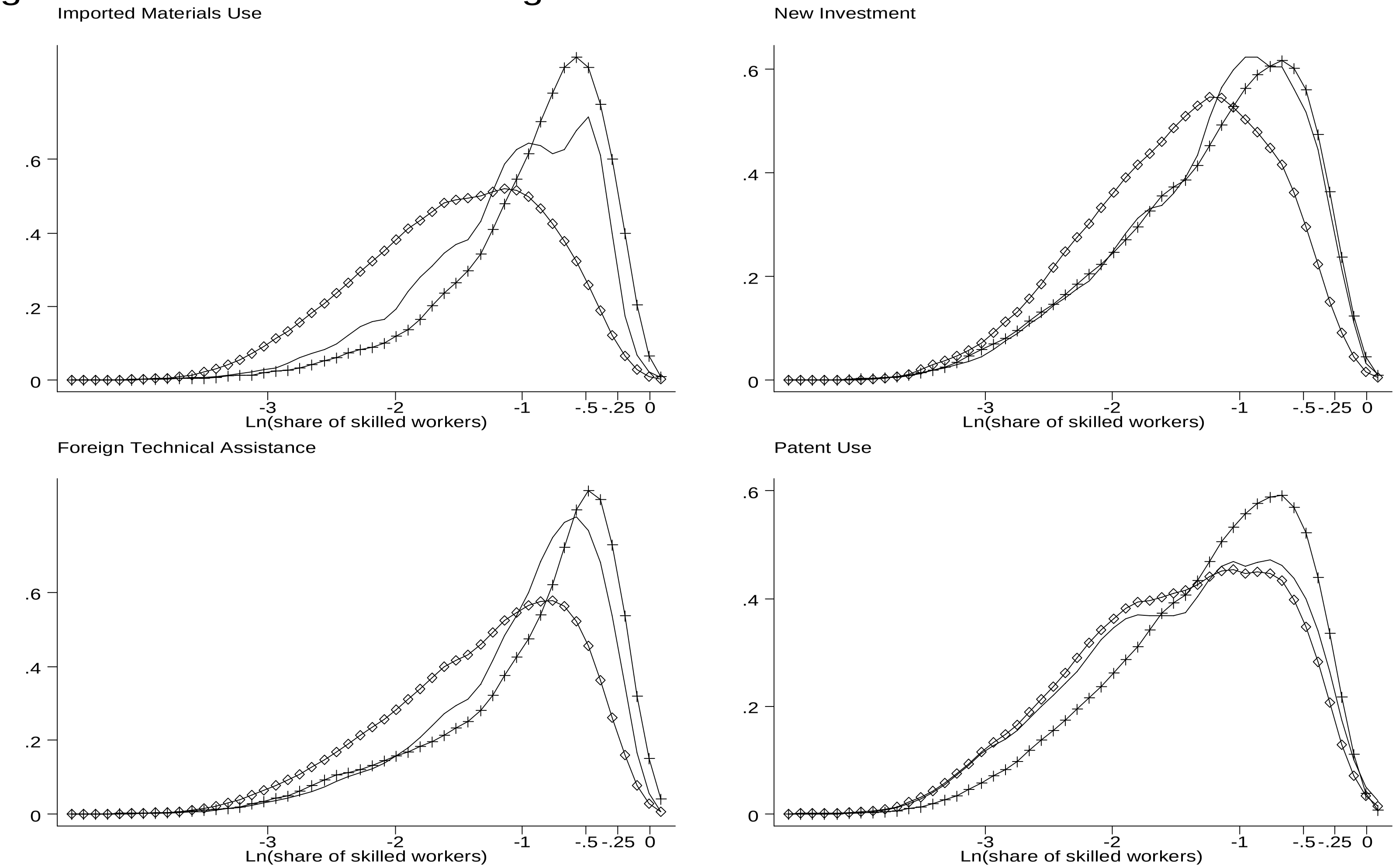
Figure 1a

Figure 1b



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

Figure2-- 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
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

Note: Quantities in thousands of 1980 pesos. Skilled and unskilled labor are measured in number of employees. There are only 24,166 observations on skilled wage because some plants do not employ any skilled workers.

Table 2--Skilled-Unskilled Labor Composition

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 figures are simple (unweighted) plant means. 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. Skill premium is the ratio of skilled wage to unskilled wage.

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
.0163	.0145	.0017	.053	.035	.018

Note: 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 Ha: 1986>1979.

Table 5--Skill Upgrading Regressions

	(1)	(2)	(3)	(4)	(5)	(6)
ln(capital/Value added)	.021 **	.009 **	.011 **	.022 **	.009 **	.011 **
	(.001)	(.002)	(.003)	(.001)	(.002)	(.003)
ln(Value added)	.046 **	.007 **	.012 **	.049 **	.007 **	.011 **
	(.001)	(.002)	(.004)	(.001)	(.002)	(.004)
FTA Indicator	.021 **	-.003	.000			
	(.005)	(.005)	(.010)			
Patent Indicator	.016 **	.002	.003			
	(.002)	(.002)	(.004)			
Imported Materials Indicator	.047 **	-.003	-.003			
	(.003)	(.003)	(.006)			
FTA Cost/Value Added				.196 **	-.004	-.065
				(.063)	(.028)	(.093)
Patent Cost/Value Added				.004 **	.001 **	.002 *
				(.001)	(.000)	(.001)
Imported Mat./Materials				.087 **	-.001	.004
				(.007)	(.007)	(.012)
Plant Indicators	no	yes	no	no	yes	no
Industry Indicators	yes	no	no	yes	no	no
Area Indicators	yes	no	no	yes	no	no
Year Indicators	yes	yes	yes	yes	yes	yes
R^2 (adjusted)	.480	.800	.003	.480	.800	.003
N	26,513	26,513	5,842	26,513	26,513	5,842

Note: The dependent variable is share of skilled workers in wage bill. Huber-White standard errors are in parenthesis. ** and * indicate significance at a 5% and 10% level, respectively. FTA stands for foreign technical assistance. The regressions in columns 3 and 6 estimate equation 1 in 5-year differences.

Appendix Table A.1--Skill upgrading regressions with industry interactions

	(1)	(2)
ln(capital/Value Added)	.017 **	.007 **
	(.001)	(.002)
ln(cap/Value Added)*textiles	.003	.000
	(.002)	(.003)
ln(cap/Value Added)*wood	-.002	.005
	(.003)	(.003)
ln(cap/Value Added)*paper	.008 *	-.001
	(.005)	(.007)
ln(cap/Value Added)*chemicals	-.004	.001
	(.003)	(.004)
ln(cap/Value Added)*glass	.011 **	.009
	(.005)	(.007)
ln(cap/Value Added)*basic metals	.030 **	.005
	(.005)	(.005)
ln(cap/Value Added)*machinery	.013 **	.006
	(.003)	(.004)
ln(cap/Value Added)*other manuf.	.028 **	.002
	(.007)	(.009)
ln(Value Added)	.043 **	.004 **
	(.002)	(.002)
ln(Value Added)*textiles	.003	.002
	(.002)	(.003)
ln(Value Added)*wood	-.006 **	.005 *
	(.003)	(.003)
ln(Value Added)*paper	.016 **	.002
	(.004)	(.004)
ln(Value Added)*chemicals	.000	.004
	(.003)	(.003)
ln(Value Added)*glass	.014 **	.008 **
	(.004)	(.004)
ln(Value Added)*basic metals	.008 *	.005 *
	(.004)	(.003)
ln(Value Added)*machinery	.012 **	.004
	(.002)	(.003)
ln(Value Added)*other manufacturing	.017 **	.008 **
	(.007)	(.004)
FTA Indicator	.019 **	-.003
	(.005)	(.005)
Patent Indicator	.016 **	.002
	(.002)	(.002)
Imported Material Indicator	.045 **	-.004
	(.003)	(.003)
Plant Indicators	no	yes
Industry Indicators	yes	no
Area Indicators	yes	no
Year Indicators	yes	yes
R^2 (adjusted)	.49	.80

Note: Huber-White standard errors are in parenthesis. ** and * indicate significance at a 5% and 10% level, respectively. FTA stands for foreign technical assistance. N is 26,513.