Knowledge Spillovers and Spatial Concentration of High Skill-Intensive Production: The Chilean Case

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Abstract: Knowledge spillovers are an important source of economic growth. This study identifies a mechanism through which knowledge spillovers occur among plants in the Chilean manufacturing industry. A plant-level production function is estimated with the absorptive-capacity hypothesis, i.e. employment of skilled workers is a key channel through which knowledge is transmitted across plants. Results show that a plant's productivity increases with its skill intensity, which is measured by the share of skilled workers in total employment. We also find that a plant's skill intensity is positively correlated with its capital stock, raw productivity, regional knowledge stock and regional population. Our results suggest that an increase in regional knowledge stock is the most effective policy to improve a plant's productivity. However, policies which encourage a plant to employ high skill-intensive production also enhance its productivity.

Key words: Knowledge spillovers; Plant's productivity; Skill intensity.

JEL codes: R11, O18, O15

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1. Introduction

The accumulation of knowledge, a non-rival and partially non-excludable good, is a key determinant of economic growth of nations (Barro and Sala-i-Martin 2003; Romer 1990; Lucas 1988). Not surprisingly, many empirical studies have found that the emergence of multi-purpose technologies, e.g. computers, and the increased globalization have raised the knowledge- or skill-intensity of production processes (Berman et al. 1994; Feenstra and Hanson 1997).[1] However, the growth and trade literature often assume that the resulting economic gains apply uniformly across firms or regions of a country. In fact, wide disparities exist in the level and types of economic activity among firms or regions within a country (Bernard and Jensen 1997; Henderson et al. 2001). In light of regional and firm heterogeneity, factors contributing to high skill-intensive production and its spatial concentration (e.g. Silicon Valley in the United States or Bangalore in India) have received substantial empirical attention (Audretsch and Feldman 1996; Audretsch and Feldman 2004).

In this study, we focus on factors raising plants' skill-intensity of production in the context of a developing economy. The distinguishing feature of developing countries is their recent urbanization accompanied by rapid accumulation of skilled workers in cities (Henderson 1986; Henderson et al. 2001). In explaining the above phenomenon, Henderson (1986) finds that (i) high skill-intensive industries tend to locate in large cities and (ii) labor demand is biased toward skilled worker when city size increases. A factor causing skill bias in labor demand is cities' specialization in high skill-intensive production by outsourcing less skill-intensive processes. In addition to the outsourcing, knowledge spillovers are considered to be a key source

of the skill bias of labor demand in large cities. The objective of this study is to identify the mechanism behind the accumulation of high-skill intensive production in specific regions by focusing on the partial non-excludability of knowledge, i.e. spillovers, as a causal factor. A better understanding of the underlying process is necessary in the search for regional polices to encourage high skill-intensive production.

Evidence of knowledge spillovers' contribution to economic growth has been found at the national and industry levels, but the majority of studies rely on a wage hedonic equation to examine the existence of spillovers (Ciccone and Peri, 2006; Moretti, 2004b; Moretti 2004c; Rauch, 1993; Acemoglu and Angrist, 2000). An exception here is the work by Moretti (2004a), whose production-function estimates show that U.S. manufacturing plants' productivity increases by 0.6-0.7 percent as the share of college graduates in a region increases by one percent. Nevertheless, issues such as the mechanism by which spillovers occur and benefit plants, and whether or not every plant can equally benefit from spillovers have received limited attention in the literature. Clarifying the spillover mechanism will help identify the type of plants which benefit from spillovers. Such economic analysis can then guide effective policies to augment knowledge spillovers, which eventually contributes to regional economic development.

We draw on the absorptive-capacity hypothesis of Cohen and Levinthal (1989) to identify the mechanism by which knowledge spillovers enhance plants' productivity. The absorptive-capacity hypothesis argues that firms must invest in research and development in order to access new knowledge created by either other firms or the public sector. Firm-level evidence on the absorptive-capacity hypothesis can be found in Arora and Gambardella (1994) and Cockburn and Henderson (1998). We extend the notion of absorptive capacity to the case of skilled workers, meaning such workers' presence is a key channel by which knowledge is transmitted across

firms or plants (Malecki 1997; Schmidt 2005). Malecki (1997) argues that technological capability embodied in skilled workers is necessary for firms to evaluate new external technologies. Furthermore, Audretsch and Feldman (1996) find empirical evidence at the industry level that high skill-intensive industries are likely to agglomerate because they tend to benefit more from spillovers than low skill-intensive industries.

Chile provides an interesting case study of spatial patterns of skill-intensive production. South American countries are considered to be the most urbanized in the developing world (United Nations 2008). Chile is not an exception since its population and skilled workers are highly concentrated in a few regions. Figure 1 shows the 1998-2003 average number of skilled workers employed in the manufacturing industry by county. The geographical distribution of skilled worker is not uniform within Chile, whose northern and central counties tend to have a higher concentration of skilled workers relative to others. This skewed geographical distribution of skilled worker leads to agglomeration of plants employing high skill-intensive production, which in turn should attract skilled workers to the region, leading to further accumulation of skilled workers. Figure 2 shows the kernel density estimates for plants' skill intensity, defined as the share of skilled workers in total workers, in counties whose regional skill intensity is above (below) the third (first) quartile of the distribution. From figure 2, it is apparent that high skill-intensive plants appear to concentrate in counties with a large share of skilled workers.

In the following, we first outline how a plant-level production function can be extended to incorporate absorptive capacity. Then, we detail the estimation and testing of plant-level production functions with and without such capacity. The estimates of the plant-level production function allows us to quantify the effect of regional and plant characteristics (e.g. regional

knowledge stock, capital stock) on a plant's choice of skill intensity. Finally, we numerically evaluate the relative contribution of regional and plant characteristics to a plant's productivity.

2. Conceptual and Empirical Framework

2.1. A Plant-Level Production Function with Absorptive Capacity

To see how the absorptive-capacity hypothesis contributes to the agglomeration of high skill-intensive production, consider the following production function of a plant:

(1) $$Y = A\left(L^s\right)^{\rho}\left(L^u\right)^{\theta},$$

where Y, L^s and L^u are output, skilled and unskilled worker, respectively, $\rho > 0$ and $\theta > 0$ are parameters characterizing the production function and A represents productivity from spillovers (externalities) defined as follows:

(2) $$A = e^{\lambda\eta S},$$

where λ is a parameter, S measures regional knowledge stock accessible to a plant and η measures plant's skill intensity, i.e., $\eta = L^s \big/ \left(L^s + L^u\right)$. If $\lambda > 0$, then $\partial A \big/ \partial L^s > 0$ and $\partial^2 A \big/ \partial L^{s2} < 0$, implying that A increases with the employment of skilled workers but at a decreasing rate (Cohen and Levinthal 1989). Equation (2) shows two channels through which A can be improved. The first channel is, of course, to increase regional knowledge stock, S. Besides this, the effect of spillovers becomes large by increasing plant's skill intensity, η, as plants can absorb external knowledge more efficiently. Given equation (1) and (2), consider the following profit maximization by a representative plant:

(3) $$\begin{aligned}\max_{L^s, L^u} \quad & e^{\lambda\eta S}\left(L^s\right)^{\rho}\left(L^u\right)^{\theta} - w_s L^s - w_u L^u \\ &= e^{\frac{\lambda S L^s}{L^s + L^u}}\left(L^s\right)^{\rho}\left(L^u\right)^{\theta} - w_s L^s - w_u L^u,\end{aligned}$$

which yields the following first order conditions:

(4) $$e^{\lambda\eta S} L^{s\rho-1} L^{u\theta} \left(\rho \left(L^s + L^u \right)^2 + \lambda S L^s L^u \right) - w_s \left(L^s + L^u \right)^2 = 0 \text{ and}$$

(5) $$e^{\lambda\eta S} L^{s\rho} L^{u\theta-1} \left(\theta \left(L^s + L^u \right)^2 - \lambda S L^s L^u \right) - w_u \left(L^s + L^u \right)^2 = 0,$$

where w_s and w_u are wage rate of skilled and unskilled worker with output price as the numeraire, respectively. Then, the ratio of skilled to unskilled worker is obtained by solving equation (4) and (5) for L^s / L^u :

(6) $$\frac{L^s}{L^u} = \frac{B + \sqrt{B^2 + 4\rho\theta}}{2\theta},$$

where $B = \rho - \theta + \lambda S$.[2] Finally, differentiating equation (6) with respect to regional knowledge stock, *S*, we have:

(7) $$\frac{\partial L^s / L^u}{\partial S} = \left(1 + \frac{B}{\sqrt{B^2 + 4\rho\theta}} \right) \frac{\lambda}{2\theta} > 0.$$

Equation (7) shows that a plant would employ more skilled workers in a region where knowledge stock is abundant. Also, note that when $\lambda = 0$, i.e. the case where absorptive-capacity hypothesis does not hold, the right hand side of equation (7) is zero and the ratio of skilled to unskilled worker is not affected by regional knowledge stock.

2.2. Estimation of a Plant-Level Production Function with Knowledge Spillovers

To test the existence of knowledge spillovers and identify the channel through which spillovers affect plant-level productivity, we extend equation (1) and (2) to an empirical setting and consider the following Cobb-Douglas production function:

$$\ln Y_{ijrt} = \beta_0 + \beta_1 \ln L^s_{ijrt} + \beta_2 \ln L^u_{ijrt} + \beta_3 \ln M_{ijrt} + \beta_4 \ln E_{ijrt} + \beta_5 \ln K_{ijrt} + \beta_6 S_{ijrt} + \beta_7 \eta_{ijrt} S_{ijrt} + \beta_8 \ln MP_{rt} + d_j + d_R + d_t + \omega_{ijrt} + \varepsilon_{ijrt}, \tag{8}$$

where Y_{ijrt}, L^s_{ijrt}, L^u_{ijrt}, M_{ijrt}, E_{ijrt} and K_{ijrt} represent output, skilled worker, unskilled worker, material, energy and capital of plant *i* belonging to 2-digit industry *j* in the *r*-th region at period *t*. *R* denotes the province to which *r*-th region belongs (Levinsohn and Petrin 2003).[3] Fixed effects d_j, d_R and d_t denote 2-digit industry, provincial and year dummies, respectively. The variable S_{ijrt} measures regional knowledge stock accessible to a plant, which is measured by the distance-weighted share of skilled workers in total workforce:

$$S_{ijrt} = \frac{\left(L^s_{jrt} - L^s_{ijrt}\right) + \sum_{q \neq r}\left(L^s_{jqt} / d_{rq}\right)}{\left(L^s_{jrt} - L^s_{ijrt}\right) + \sum_{q \neq r}\left(L^s_{jqt} / d_{rq}\right) + \left(L^u_{jrt} - L^u_{ijrt}\right) + \sum_{q \neq r}\left(L^u_{jqt} / d_{rq}\right)}, \tag{9}$$

where L^s_{jrt} and L^u_{jrt} are respectively the number of skilled and unskilled workers in industry *j* in the *r*-th region at time *t*. We subtract own plant's skilled (skilled and unskilled) workers when computing the numerator (denominator). As a region used in this study is an administrative geographical unit, economic interaction among plants may not be complete within a region. Rather, knowledge stock in any other region ($q \neq r$) affects the productivity of plants in the *r*-th region with its effect decaying as distance between the two regions increases (Lopez-Bazo et al. 2004). Hence, in equation (9), we include skilled and unskilled workers in region $q \neq r$ weighted by d_{rq}, the great-circle distance between region *r* (base) and *q* in kilometers (Crozet et al. 2004). Note S_{ijrt} approaches one (zero) as skilled (unskilled) workers are abundant in the surrounding regions.

In equation (8), S_{ijrt} is scaled by our measure of the absorptive capacity, η_{ijrt}, which is the share of skilled workers to total workers of plant *i* (equation 2). If β_7 is positive and

significant, high skill-intensive plants gain more from knowledge spillovers than others and the absorptive-capacity hypothesis is empirically supported. On the contrary, if the absorptive-capacity hypothesis is not valid and every plant, regardless of its skill intensity, benefits from spillovers, then β_6 would be positive and significant. Finally, MP_{rt} is the distance-weighted regional population:

$$(10) \qquad MP_{rt} = Pop_{rt} + \sum_{q \neq r} \left(\frac{Pop_{qt}}{d_{rq}} \right),$$

where, Pop_{rt} denotes population in *r*-th region at period *t*. The new economic-geography literature has well documented the productivity-enhancement effect of agglomeration economies, which are externalities arising from ease of input- and output-market access (Baldwin et al. 2003; Fujita et al. 1999). Equation (10) provides a distance-weighted measure to take into account of the effect from surrounding regions.

The plant's raw productivity, ω_{ijrt}, is defined as plant- and time-specific productivity shock and ε_{ijrt} is an *i.i.d.* disturbance term (Levinsohn and Petrin 2003). A plant's productivity shock is not observable to us, but it may pose a problem in the consistent estimation of the parameters of equation (8) (Levinsohn and Petrin 2003; Olley and Pakes 1996). For example, a plant realizing a positive productivity shock may respond by using more workers or material (intermediate) inputs to increase its output. As ω_{ijrt} is likely correlated with conventional input use, ordinary least squares (OLS) estimation of equation (8) where the productivity shock, ω_{ijrt}, is added to the *i.i.d.* disturbance, ε_{ijrt}, would result in inconsistent parameter estimates of the production function.

To correct this problem, we employ the Levinsohn and Petrin's (2003) approach. Given plants' predetermined capital stock and locational attributes, S_{ijrt}, plants first realize their productivity level and then, choose the level of conventional inputs (Fernandes 2007; Yasar and Morrison 2007). For this purpose, we assume that material (intermediate) input use is a monotonic function of productivity:

$$\ln M_{ijrt} = m\left(\omega_{ijrt}, \ln K_{ijrt}, S_{ijrt}, \ln MP_{rt}\right). \tag{11}$$

Then, we can invert equation (11) and express the productivity shock as a function of material input, capital stock and locational attributes:

$$\omega_{ijrt} = \omega\left(\ln M_{ijrt}, \ln K_{ijrt}, S_{ijrt}, \ln MP_{rt}\right). \tag{12}$$

By substituting (12) into (8):

$$\begin{aligned} \ln Y_{ijrt} = {} & \beta_1 \ln L^s_{ijrt} + \beta_2 \ln L^u_{ijrt} + \beta_4 \ln E_{ijrt} + \beta_7 \eta_{ijrt} S_{ijrt} + d_j + d_R + d_t \\ & + \varphi\left(\ln M_{ijrt}, \ln K_{ijrt}, S_{ijrt}, \ln MP_{rt}\right) + \varepsilon_{ijrt}, \end{aligned} \tag{13}$$

where:

$$\begin{aligned} \varphi\left(\ln M_{ijrt}, \ln K_{ijrt}, S_{ijrt}, \ln MP_{rt}\right) = {} & \beta_0 + \beta_3 \ln M_{ijrt} + \beta_5 \ln K_{ijrt} + \beta_6 S_{ijrt} + \beta_8 \ln MP_{rt} \\ & + \omega\left(\ln M_{ijrt}, \ln K_{ijrt}, S_{ijrt}, \ln MP_{rt}\right). \end{aligned} \tag{14}$$

Since ε_{ijrt} is assumed to be independent of L^s, L^u and E, we can consistently estimate β_1, β_2, β_4 and β_7 by approximating $\varphi(\cdot)$ with a second-order polynomial and using OLS.

Following Levinsohn and Petrin (2003), we proceed to a second stage, where the productivity shock follows a first-order Markov process, to identify β_3, β_5, β_6 and β_8. That is, production function, equation (8), at period $t+1$ is written as:

$$\begin{aligned} \ln Y_{ijrt+1} = {} & \beta_1 \ln L^s_{ijrt+1} + \beta_2 \ln L^u_{ijrt+1} + \beta_3 \ln M_{ijrt+1} + \beta_4 \ln E_{ijrt+1} + \beta_5 \ln K_{ijrt+1} + \beta_6 S_{ijrt+1} \\ & + \beta_7 \eta_{ijrt+1} S_{ijrt+1} + \beta_8 \ln MP_{rt+1} + d_j + d_R + d_{t+1} + g\left(\omega_{ijrt}\right) + \varepsilon_{ijrt+1} + \xi_{ijrt+1}. \end{aligned} \tag{15}$$

where, ξ_{ijrt+1} is an innovation. From equation (14), we can express plant's productivity as follows:

(16) $$\beta_0 + \omega_{ijrt} = \hat{\varphi}(\cdot) - \beta_3 \ln M_{ijrt} - \beta_5 \ln K_{ijrt} - \beta_6 S_{ijrt} - \beta_8 \ln MP_{rt}.$$

Given $\hat{\beta}_1$, $\hat{\beta}_2$, $\hat{\beta}_4$, $\hat{\beta}_7$ and ω_{irt} from the equation (16), we can consistently estimate β_3, β_5, β_6 and β_8 by approximating $g(\cdot)$ with a third-order polynomial and using nonlinear instrumental-variables estimator. Instrumental variables estimator is preferred because $\varepsilon_{ijrt+1} + \xi_{ijrt+1}$ is correlated with $\ln M_{ijrt+1}$. We use $\hat{\varphi}\left(\ln M_{ijrt}, \ln K_{ijrt}, S_{ijrt}, \ln MP_{rt}\right)$, $\ln K_{ijrt+1}$, $\ln K_{ijrt}$, $\ln M_{ijrt}$, $\ln E_{ijrt}$, S_{ijrt+1} and $\ln MP_{rt+1}$ as instruments. Given the multiple steps in the estimation, the standard error of parameter estimates is obtained using bootstrapping procedures.[4]

2.3. Plants' Skill Intensity and Regional Knowledge Stock

Having illustrated a technological framework to capture knowledge spillovers in plant's productivity, we now turn our attention to the role of such spillovers in enhancing plants' skill intensity. Recall that if the estimate of β_7 is positive and significant, then high skill-intensive plants can benefit more from spillovers than other plants. Therefore, plants are willing to employ more skilled workers than unskilled workers as shown in equation (7) if they locate in a region with a large knowledge stock. In this section, we evaluate how much knowledge spillovers contribute to raising a plant's skill intensity. Levinsohn and Petrin (2003) show that the log of conventional inputs' level (e.g. material inputs) is a function of predetermined capital, plant's raw productivity and locational attributes (equation 11). Similarly, other conventional inputs such as skilled and unskilled worker are determined as follows:

(17) $\ln L^s_{ijrt} = L^s\left(\omega_{ijrt}, \ln K_{ijrt}, S_{ijrt}, \ln MP_{rt}\right)$ and

(18) $\ln L^u_{ijrt} = L^u\left(\omega_{ijrt}, \ln K_{ijrt}, S_{ijrt}, \ln MP_{rt}\right)$.

To focus on the direct effect of these variables on demand for each type of workers, we employ a first-order approximation of equation (17) and (18) (Olley and Pakes 1996). By subtracting the specified first-order approximation of equation (18) from (17), we have:

(19) $$\ln \frac{L^s_{ijrt}}{L^u_{ijrt}} = \alpha_1 + \alpha_2 \ln \frac{w^s_{rt}}{w^u_{rt}} + \alpha_3 S_{ijrt} + \alpha_4 \ln MP_{rt} + \alpha_5 \omega_{ijrt} + \alpha_6 \ln K_{ijrt} + d_j + d_R + d_t + v_{ijrt},$$

where v_{ijrt} is the *i.i.d.* disturbance. The wage rates for skilled and unskilled worker, w^s_{rt} and w^u_{rt} respectively, are indexed by region and time. Plant's raw productivity, ω_{ijrt}, is obtained from equation (16).

If ease of input- and output-market access in a large city leads to outsourcing of less skill-intensive processes and the specialization in high skill-intensive production as Henderson (1986) argues, regional market size and plant's skill intensity should be positively correlated. Moreover, recent contributions to the new economic geography literature show that high-ability workers self-select into an area with large population (Combes et al. 2008). Thus, a region with a large share of skilled worker is also likely to have a large population. Therefore, controlling for regional population, MP_{rt}, in equation (19) mitigates a potential simultaneity problem between regional market size and regional skill intensity. Next, we anticipate that plants in a region with a large knowledge stock, where supply of skilled worker is relatively abundant, might employ more skilled workers because of their low relative wage. In other words, high skill-intensive production in a region with a large knowledge stock might be the consequence of low relative wage for skilled workers rather than spillovers. To control the wage effect on plant's skill intensity, relative wage is included in the estimation of equation (19). Finally, industry fixed

effects will control for the difference in skill intensity observed at the industry level, which also explains the agglomeration of high skill-intensive production in cities (Henderson, 1986).

It is likely that a shock to a plant's relative labor demand may also affect the regional knowledge stock. For example, a positive shock on a plant's relative labor demand may attract skilled workers and increase a region's share of skilled workers. Moreover, a high skill-intensive plant may locate in a relatively high skill-intensive region. Thus, regional knowledge stock, *S*, must be instrumented when estimating equation (19). We employ the average years of education of workers in a previous year as the instrument (see section 4.2.). Finally, equation (17) and (18) do not assume path dependency of absorptive capacity. Plants need to be continuously high skill-intensive to maximize the benefit from spillovers (Schmidt 2005). In other words, high skill-intensive plants at previous periods should employ a large number of skilled workers in the current period to keep their high capacity for absorbing external knowledge. Hence, we check for path dependency in plants' relative skill intensity by adding the lagged plant's skill intensity, η_{t-1}, to the right hand side of equation (19). The presence of the lagged plant's skill intensity in equation (19) also helps mitigate the possible endogeneity problem arising from the self-selection of a high skill-intensive plant into a relatively high skill-intensive region.

2.4. Evaluation of Spillovers' Effect on Plant's Productivity

The above two subsections show that plants increase their skill intensity to benefit from spillovers in a region with a large knowledge stock. Thus, an increase in plant's productivity from spillovers can be decomposed into direct and indirect effect, the latter arising from increasing plant's skill intensity, as follows:[5]

$$
\begin{aligned}
\frac{\partial \ln A}{\partial \ln S} &= \frac{\partial\left(\beta_6 S + \beta_7 \eta S\right)}{\partial \ln S} \\
&= \left(\beta_6 + \beta_7 \eta\right)\frac{\partial S}{\partial \ln S} + \beta_7 S \frac{\partial \eta}{\partial \ln S} \qquad (20) \\
&= \left(\beta_6 + \beta_7 \eta\right) S + \alpha_3 \beta_7 \eta \left(1-\eta\right) S^2,
\end{aligned}
$$

where the first term of the third line of equation (20) measures the direct effect, while the second term represents the indirect effect. Furthermore, other explanatory variables in equation (19), i.e., plant's capital stock, raw productivity, e^{ω}, regional population and relative wage, also affect plant's productivity from spillovers through increasing or decreasing plant's skill intensity (equation 19):

$$
\begin{aligned}
\frac{\partial \ln A}{\partial \ln K} &= \frac{\partial\left(\beta_6 S + \beta_7 \eta S\right)}{\partial \ln K} \\
&= \beta_7 S \frac{\partial \eta}{\partial \ln K} \qquad (21) \\
&= \alpha_5 \beta_7 \eta \left(1-\eta\right) S,
\end{aligned}
$$

Equation (21) shows the effect of a plant's capital stock on its productivity from spillovers, *A*. Effects of plant's raw productivity, regional population and relative wage on *A* can be obtained in a way similar to that of equation (21).

3. Chilean Data

We use data from the annual *Chilean Manufacturing Census* from 1998 to 2003 collected by National Statistics Institute (INE). Plants with at least 10 employees are surveyed in the Census, with information on plant location at three administrative levels: macro-region, province and county. We use each of the 342 counties as a geographical unit (region) to assure enough variation in data and to take account of geographical distribution of plants within a macro-region or a province, which is obscured if we use macro-region or province as a geographical unit.

However, since county is a small administrative geographical unit, interregional spillovers are likely to exist and therefore, we need to take into account of economic conditions in other regions (equation 9 and 10).

Six variables are constructed to estimate the plant-level production function: skilled worker, unskilled worker, materials, energy, capital and output.[6] The unit of worker is the number of workers, while other variables are in Chilean Peso. We use deflators (base year 1996) from the *Chilean National Accounts* to convert the latter variables into constant Chilean Peso. As a measure of regional knowledge stock, we use the distance-weighted share of skilled worker, S_{SKL1} (equation 9). Since skilled workers are crucial to R&D and development of new products (Malecki, 1997) and are more educated than unskilled workers (see Appendix B), it is plausible to assume that a region with a large share of skilled worker has a large regional knowledge stock. However, as figure 1 shows, economic activity in Chile concentrate in the Santiago Metropolitan macro-region, which accounts for 40 percent of the national population. The large number of workers in the Santiago macro-region may have a huge impact in constructing regional skill intensity, S_{SKL1}, even in regions far from the Santiago macro-region. To check if this affects the results, we construct another variable, S_{SKL2}. In constructing S_{SKL2} in r-th county, we only use data from counties within the macro-region to which r-th county belongs. In addition, another alternative measure of regional knowledge stock in r-th county, S_{SKL3}, is constructed using data from r-th county only, i.e., we do not assume any interregional spillovers. Similarly, three alternative measures of MP_{rt} are constructed from *Population Projections*, INE. MP_1 is the distance-weighted county population, MP_2 is the distance-weighted county population within a macro-region and MP_3 is county population. Finally, county wages for skilled (unskilled) worker used in the estimation of equation (19) are obtained by dividing the total wage bill for

skilled (unskilled) workers of all plants in a county by the total number of skilled (unskilled) workers. Summary statistics on each of the variables used in this study are presented in table 1. In addition to mean and standard deviation of variables, the mean of coefficient of variation of each variable across plants or county-isic pairs for each year and the mean of coefficient of variation across time for each plant or county-ISIC pair are presented to see how much the variation in each variable is attributed to cross-sectional and time-series variations. Note that regional characteristics such as regional skill intensity, S_{SKL}, and regional population, MP, show small variance across time, implying time persistence in those variables.

4. Results

4.1. Production Function Estimates

We first discuss the estimates of the plant-level production function estimated under the assumption of absorptive capacity. Table 2 shows the parameter estimates of the production function in equation (8) for the Chilean manufacturing industry. Column (1) shows the result of the estimation with the distance-weighted share of skilled worker, S_{SKL1}, the first of the three measures of regional knowledge stock. The results with the distance-weighted share of skilled worker within a macro-region, S_{SKL2}, and the share of skilled worker in a county, S_{SKL3}, are shown in column (2) and (3), respectively. Estimated parameters on conventional inputs –skilled and unskilled workers, materials, energy and capital- are positive and statistically significant in every specification. Similar to plant-level studies of other countries, e.g., Henderson (2003), Chilean manufacturing plants show high intensity of material inputs in production. Returns to scale, which is defined as the sum of coefficients on conventional inputs, is in the range of 1.02-1.03 and the null hypothesis that technology exhibits constant returns to scale is not rejected.

Our specification of absorptive capacity appears to well fit the data since the parameter on ηS is positive and statistically significant for all specifications. On the contrary, the parameter on S is not statistically significant. This result is consistent with the argument that high skill-intensity is necessary for a plant to utilize new knowledge created by other plants in the industry presumably through the interaction among skilled workers, i.e., absorptive capacity (Cockburn and Henderson, 1998; Cohen and Levinthal, 1989). In other words, we find evidence that the presence of high-skilled workers serves as an important channel through which knowledge is transmitted across plants. Multiplying the parameter from column (1), the base model, by plants' average skill intensity (0.32) and average regional skill intensity (0.46), we find elasticity of productivity of an average plant with respect to the share of skilled worker in a region (and surrounding regions) is 0.05. Alternatively, elasticity of plant's productivity with respect to the share of skilled worker in a region varies between 0-0.16 depending on the plant's skill intensity. In evaluating Moretti's (2004a) result at its sample mean, we know that the elasticity of the U.S. firms' productivity with respect to the share of university graduates is 0.10-0.13. Hence, the magnitude of the spillover elasticity in our study is comparable to the one in Moretti (2004a). However, unlike Moretti's (2004a) study**,** our results suggest that high skill-intensive plants benefit more from knowledge spillovers. Finally, the parameter on regional population, *MP*, is not statistically significant in all three specifications.

4.2. Plant's Skill Intensity Estimates

In this subsection, we report estimated results on plants' choice of their skill intensity. The instruments considered for the regional knowledge stock, *S*, in the estimation of equation (19) are the average years of education of workers in industry *j* in *r*-th county from the *1992 Housing and*

Population Census and a human capital index (*Regional Competitiveness Report*, Chilean Ministry of Economy, various issues). We choose these instruments because educational level at a previous period is correlated with current educational level of workers, i.e. regional knowledge stock, as long as they continue to work in the same industry and region. However, the proposed instruments do not include the educational level of newly employed workers and hence, are not correlated with a current shock to plant's relative labor demand.[7] To check the relevance of these instruments, we employ the Cragg-Donald Wald F statistic presented at the bottom of table 3. The Cragg-Donald Wald F statistic exceeds the critical value for 10 percent maximal IV size distortion when using the 1992 average years of education of workers in industry *j* in *r*-th county as the instrument for *S* (Stock and Yogo 2005).[8]

Column (1), (3) and (5) of table 3 show results from the estimation of equation (19) with the distance-weighted share of skilled worker, S_{SKL1}, the distance-weighted share of skilled worker within a macro-region, S_{SKL2}, and the share of skilled worker in a county, S_{SKL3}, respectively. The estimated parameter on the share of skilled worker in a region (and surrounding regions) is positive and significant for each specification. Thus, after controlling for the wage effect, the greater the knowledge stock of a region, the higher is the skill-intensity of plants. In other words, plants raise their skill intensity to benefit from spillovers in a region where skilled workers are abundant. Furthermore, the parameter on regional population, *MP*, is significant for all specifications, implying that plants tend to adopt high skill-intensive production in regions with a large population. In terms of plant's characteristics, both plant's raw productivity and the capital stock increase plant's skill intensity. This is consistent with Pavcnik's (2003) finding that capital is a complement to skilled workers. Prior literature also suggests that high-productivity plants tend to invest in R&D and innovation activity, which

requires relatively more skilled workers. For example, using Chilean manufacturing plant-level data, Alvarez and Robertson (2004) find a positive relationship between investment in technology and plant size, which is also positively correlated with the productivity level (Jovanovic 1982).

The above results confirm positive correlation between plant's skill intensity and regional knowledge stock. We next check path dependency of absorptive capacity by including the lagged plant's skill intensity, η_{t-1}, in equation (19). Column (2), (4) and (6) of table 3 present the estimation results, where we find that the coefficient on the lagged plant's skill intensity is positive and significant in each specification. In addition, except the result in column (6), the case where no interregional spillovers are assumed, the coefficient on regional skill intensity remains positive and significant. Thus, after controlling path dependency of absorptive capacity, we observe plants tend to employ more skilled workers in a region where the knowledge stock is large. Finally, the coefficient on relative wage is negative and significant, implying that plants employ more skilled workers in a region where relative wage of skilled worker is low, i.e., the supply of skilled labor is relatively abundant.

4.3. Regional Knowledge Stock and Plant's Productivity

From the results in previous subsections, we find that high skill-intensive plants benefit more from knowledge spillovers. Hence, plants employ more skilled workers to obtain larger benefits from spillovers in a region with a large knowledge stock. Accordingly, the effect of regional knowledge stock on plant's productivity enhancement due to spillovers is decomposed into a direct and indirect effect, the latter taking place through increasing plant's skill intensity (equation 20). Following equation (20) and (21), we evaluate both direct and indirect effects

numerically at the sample mean with estimation results in column (2), (4) and (6) of table 3. The results are presented in the column labeled "Elasticity" in table 4. The second, fourth and sixth columns are respectively the result obtained from the estimates with the distance-weighted share of skilled worker (S_{SKL1}), the distance-weighted share of skilled worker within a macro-region (S_{SKL2}) and the share of skilled worker in a county (S_{SKL3}).

In general, the direct effect of an increase in regional knowledge stock has the largest positive impact on overall plant's productivity from spillovers followed by the indirect effect of an increase in regional knowledge stock. Sum of direct and indirect effect of an increase in regional knowledge stock is 0.09, 0.09 and 0.03 from the second, fourth and sixth column, respectively. Thus, as the share of skilled worker in a region (and surrounding regions) increases by one percent, plant's overall productivity from spillovers increases by 0.03-0.09 percent. Lall et al. (2004) estimation of a plant-level production function using Indian data shows that the elasticity of localization economies (externalities arising from the agglomeration of the same industry) ranges between 0.04-0.10 depending on the industry. Hence, after controlling for the indirect effect, the elasticity of knowledge spillovers for the average plant in Chile is numerically comparable to the result obtained in the case of India. Note however that our study differs from previous studies in clarifying the spillover mechanism. Our results clearly show knowledge spillovers under absorptive capacity hypothesis are important in explaining the skill-biased labor demand in developing countries. In other words, in order to enhance knowledge spillovers, plants in a region with a large knowledge stock must raise their absorptive capacity, i.e. employ more skilled workers.

We also compute the change in plant's overall productivity from spillovers due to an increase in explanatory variables such as S and K, from median to 90th percentile value.[9] Results

are presented in the column labeled "% change in productivity" in table 4. Again, direct and indirect effects from an increase in regional knowledge stock have the largest impact on plant's productivity followed by that of regional population and capital stock. Overall productivity of a plant locating in a region where the S_{SKL} is at the 90th percentile is 6.11-12.25 percent higher than overall productivity of a plant locating in a region with the median level of S_{SKL}. Next, overall productivity of a plant locating in a region where the *MP* is at the 90th percentile is 0.28-1.80 percent higher than the overall productivity of a plant locating in a region with median level of *MP*. Finally, overall productivity of a plant with the capital stock at the 90th percentile is 0.34-1.02 percent higher than the overall productivity of a plant with median level of the capital stock.

Since spillover benefits become large for plants with a high capacity for absorbing external knowledge, plants tend to employ more skilled workers to further increase their productivity. The above results indicate that this indirect effect is an important channel to enhance plant's productivity because an increase in productivity through this indirect effect is quantitatively comparable to an increase through direct effect.

5. Summary and Conclusions

Recent rapid urbanization in developing countries accompanies accumulation of skilled workers in urban areas. In this study, we examined knowledge spillovers as a source of geographical concentration of high skill-intensive production in Chile. Empirical applications of endogenous growth theory to developed countries suggest knowledge spillovers are an important source of economic growth, but few studies have focused on developing economies. Moreover, the mechanism by which knowledge spreads across firms or plants has received limited empirical attention in both developed- and developing-country studies. To address this gap in the literature,

we extended the absorptive-capacity hypothesis, i.e. own investment in skills is required to utilize knowledge created by other firms, to a plant-level setting. We anticipated that high skill-intensive plants benefit more from spillovers than their low-skill counterparts, which lead to concentration of high skill-intensive plants in a region where the knowledge stock is abundant.

To test the absorptive-capacity hypothesis, we first estimated a plant-level production function incorporating knowledge spillovers. We draw on recent approaches to estimating plant-level production functions, which account for the correlation between unobserved plant's productivity and conventional input use. Our estimates of the production function showed statistical support for the absorptive-capacity hypothesis in Chilean manufacturing industries, i.e. high skill-intensive plants benefit from spillovers. In other words, plants' heterogeneity in terms of skill intensity matters for knowledge spillovers in developing countries. Moreover, the economic significance of knowledge spillovers to manufacturing plants' productivity in Chile is comparable to that found in developed countries.

Since plants are expected to employ more skilled worker than unskilled worker in a region with a large knowledge stock, we next evaluated how much of plants' skill intensity increased in response to an increase in regional knowledge stock. We found that plant's skill intensity was positively correlated with the knowledge stock of a region, regional population, plant's raw productivity and the capital stock, but was negatively correlated with the relative wage of skilled workers. Finally, an increase in overall plant's productivity from spillovers was decomposed into a direct and indirect effect, the latter arising from increasing plants' skill intensity. We also evaluated the effect of plants' capital stock, raw productivity, regional population and relative wage on overall plant's productivity from spillovers through changing its skill intensity. Results showed that regional knowledge stock contributed the most to overall

plant's productivity enhancement, but the indirect effect through plants' capital stock and relative wages had a comparable magnitude.

Knowledge spillovers contribute to the agglomeration of high skill-intensive production in developing countries as high capacity to absorb external knowledge is necessary to maximize benefits from spillovers, leading to a large demand for skilled workers in cities. Our results show that educating local population is effective in the context of regional development since it raises the regional knowledge stock, the source of knowledge spillovers, and at the same time, it increases the supply of human-capital which helps plants to employ skilled worker at a low wage. Also, a policy which encourages plants to increase their skill intensity is a good instrument for regional development.

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Table 1: Summary Statistics

Variable	Unit	Mean	Std. Dev.	CV across Plants/Counties	CV across Time
Output (*Y/1,000,000*)	Constant peso	3.45	13.25	3.82	0.24
Skilled worker (L^s)	Number	23.09	66.36	2.86	0.34
Unskilled worker (L^u)	Number	50.62	104.12	2.06	0.32
Material (*M/1,000,000*)	Constant peso	1.98	8.69	4.25	0.31
Energy (*E/1,000,000*)	Constant peso	0.09	0.55	6.27	0.33
Capital (*K/1,000,000*)	Constant peso	1.67	7.18	4.27	0.20
Share of skilled worker of a plant (η)	Index, 0-1	0.32	0.24	0.76	0.33
Distance-weighted share of skilled worker in a county (S_{SKL1})	Index, 0-1	0.46	0.19	0.41	0.13
Distance-weighted share of skilled worker within a macro-region in a county (S_{SKL2})	Index, 0-1	0.45	0.26	0.57	0.28
Share of skilled worker in a county (S_{SKL3})	Index, 0-1	0.40	0.29	0.72	0.40
Distance-weighted county population (MP_1/1,000)	Number	170.83	204.76	1.20	0.02
Distance-weighted county population within a macro-region (MP_2/1,000)	Number	126.30	203.08	1.61	0.02
County population (MP_3/1,000)	Number	45.37	70.65	1.56	0.02
Relative wage for skilled worker (w_s/w_u)	Constant peso	2.41	3.56	0.84	0.28

Note: CV across plants/counties measures the coefficient of variation of each variable across plants or county-isic pairs for each year. Then, obtained coefficients are averaged over years. Similarly, CV across time measures the variation across time for each plant or county-isic pair. Then, obtained coefficients are averaged over plants or county-isic pairs. For MP_1, MP_2 and MP_3, variation is measured across counties as they are invariant across industries.
Source: INE, Chilean Manufacturing Census, Various Years.
INE, Population Projections, Various Years.

Table 2: Parameter Estimates of the Production Function

Variable	(1)	(2)	(3)
$\ln L^s$	0.089***	0.090***	0.098***
	(0.008)	(0.007)	(0.006)
$\ln L^u$	0.125***	0.125***	0.114***
	(0.009)	(0.008)	(0.007)
$\ln M$	0.631***	0.638***	0.616***
	(0.045)	(0.039)	(0.050)
$\ln E$	0.069***	0.068***	0.070***
	(0.005)	(0.005)	(0.005)
$\ln K$	0.113***	0.108***	0.124***
	(0.024)	(0.022)	(0.026)
S_{SKL1}	-0.170		
	(0.178)		
ηS_{SKL1}	0.350***		
	(0.101)		
S_{SKL2}		-0.140	
		(0.139)	
ηS_{SKL2}		0.342***	
		(0.097)	
S_{SKL3}			-0.118
			(0.083)
ηS_{SKL3}			0.181***
			(0.068)
$\ln MP_1$	-0.005		
	(0.039)		
$\ln MP_2$		0.000	
		(0.028)	
$\ln MP_3$			0.001
			(0.024)
Returns to Scale	1.027	1.029	1.021
$(\beta_2+\beta_3+\beta_4+\beta_5+\beta_6)$	(0.026)	(0.022)	(0.029)
Observations	14202	14103	12629

Note: *** indicates statistical significance at the 1%. Value in parenthesis is the bootstrapped standard error based on 200 iterations. Dependent variable is the log of output.

Table 3: Parameter Estimates of the Plants' Skill Intensity Model

Variable	(1)	(2)	(3)	(4)	(5)	(6)
$\ln(w_s/w_u)$	-0.055	-0.136***	-0.010	-0.114*	-0.122	-0.166*
	(0.059)	(0.054)	(0.070)	(0.062)	(0.088)	(0.087)
S_{SKL1}	5.643***	2.546**				
	(1.231)	(1.130)				
S_{SKL2}			5.748***	2.687**		
			(1.318)	(1.151)		
S_{SKL3}					2.597**	1.249
					(1.108)	(1.065)
$\ln MP_1$	0.117***	0.067*				
	(0.042)	(0.037)				
$\ln MP_2$			0.068*	0.052*		
			(0.040)	(0.032)		
$\ln MP_3$					0.067***	0.026
					(0.022)	(0.018)
ω	0.233***	0.144**	0.167**	0.118*	0.191*	0.141
	(0.070)	(0.064)	(0.076)	(0.067)	(0.104)	(0.092)
$\ln K$	0.020***	0.017***	0.020***	0.017***	0.010*	0.012**
	(0.005)	(0.005)	(0.006)	(0.005)	(0.006)	(0.005)
η_{t-1}		3.060***		3.047***		3.013***
		(0.034)		(0.036)		(0.042)
Constant	-5.133***	-4.099***	-4.289***	-3.850***	-3.152***	-2.999***
	(0.526)	(0.481)	(0.438)	(0.382)	(0.303)	(0.280)
Cragg-Donald Wald F	193.941	135.304	100.590	73.917	52.044	33.071
Observations	19730	14341	19623	14264	17903	13043

Note: *, ** and *** indicate statistical significance at the 10%, 5% and 1%, respectively. Value in parenthesis is the standard error. Dependent variable is the log of the ratio of skilled to unskilled worker.

Table 4: Elasticity of Productivity and Change in Productivity due to Increase in Explanatory Variables from Median to 90th percentile Value

Variable	Elasticity	% change in productivity	Elasticity	% change in productivity	Elasticity	% change in productivity
Direct effect						
Distance-weighted share of skilled worker in a county (S_{SKL1})	0.050	3.843				
Distance-weighted share of skilled worker within a macro-region in a county (S_{SKL2})			0.049	6.685		
Share of skilled worker in a county (S_{SKL3})					0.023	4.560
Indirect effect through increasing plant's skill intensity						
Distance-weighted share of skilled worker in a county (S_{SKL1})	0.040	3.048				
Distance-weighted share of skilled worker within a macro-region in a county (S_{SKL2})			0.041	5.569		
Share of skilled worker in a county (S_{SKL3})					0.008	1.549
Distance-weighted county population (MP_1/1,000)	0.002	1.101				
Distance-weighted county population within a macro-region (MP_2/1,000)			0.002	1.803		
County population (MP_3/1,000)					0.000	0.282
Capital (K)	0.001	1.020	0.001	1.024	0.000	0.340
Plant's raw productivity (e^{ω})	0.005	0.040	0.004	0.030	0.002	0.008
Relative wage of skilled worker (w^s / w^u)	-0.005	-0.288	-0.004	-0.234	-0.003	-0.159

Note: In evaluating equation (20), β_6 is set to zero as it is insignificant in the production function estimates.

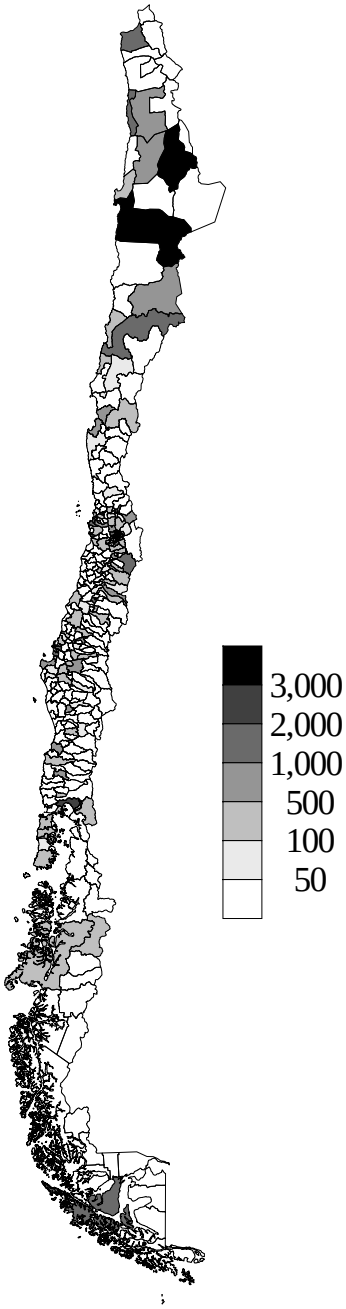

Figure 1: Average of Plants' Skill Intensity in Chilean Counties
(Unit: Number of Skilled Worker)

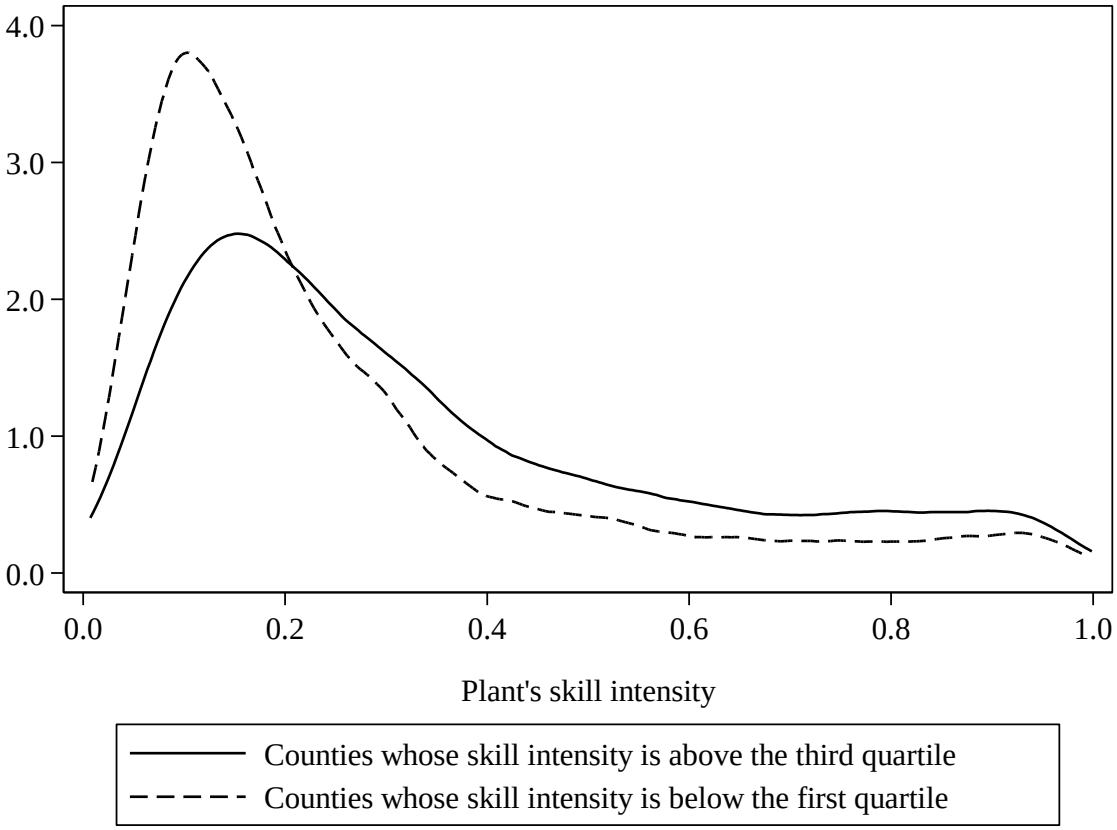

Figure 2: Kernel Density Estimates for Plants' Skill Intensity in Counties Whose Skill Intensity is above (below) the Third (First) Quartile

Appendix A: Derivation of Equation (20)

In this appendix, we show how the third line of equation (20) is derived. First of all, the derivative of plant's skill intensity with respect to the log of regional knowledge stock is obtained as follows:

$$
\begin{aligned}
\frac{\partial \eta}{\partial \ln S} &= \frac{\partial \eta}{\partial \ln \eta} \frac{\partial \ln\left(L^s / \left(L^s + L^u\right)\right)}{\partial \ln S} \\
&= \eta \frac{\partial \ln\left(1 + L^u / L^s\right)^{-1}}{\partial \ln S} \\
&= -\eta \left(1 + L^u / L^s\right)^{-1} \frac{\partial\left(1 + L^u / L^s\right)}{\partial \ln S} \\
&= -\eta \frac{L^s}{L^s + L^u} \frac{\partial L^u / L^s}{\partial \ln L^u / L^s} \frac{\partial \ln\left(L^s / L^u\right)^{-1}}{\partial S} \frac{\partial S}{\partial \ln S} \\
&= -\eta \frac{L^s}{L^s + L^u} \frac{L^u}{L^s} \left(-\alpha_3\right) S \\
&= \alpha_3 \eta \left(1 - \eta\right) S.
\end{aligned}
\tag{A1}
$$

The derivative of the log of the ratio of skilled to unskilled worker in the fourth line is α_3 from equation (19). The fifth line is obtained by using this parameter. Substituting equation (A1) into the second line of equation (20) yields the third line of equation (20). Also, the third line of equation (21) is obtained in a similar way.

Appendix B: Construction of Plant-Level Variables

Output is defined as the sum of revenue, sales of electricity and value of self-produced capital goods. Inventory is adjusted in the construction of output. Material is the sum of raw materials' value, goods purchased for resale and the cost of work by third parties. Energy is the sum of purchase values of electricity, water and fuel. Output and input variables in values are converted to constant price by using price deflator (base year 1996) from the *Chilean National Accounts*, which is available on the Central Bank of Chile's webpage. Output is deflated by the deflator for gross output, while material and energy are deflated using the deflator for intermediate goods.

Skilled (unskilled) worker comprises of workers reported as white (blue) collar in the *Chilean Manufacturing Census*. White-collar workers include executives, administrative, white-collar production employees, while blue-collar workers include both blue-collar production and nonproduction employees (e.g. clerks, secretaries). Although *Manufacturing Census* does not provide data on worker's education, *2002 Housing and Population Census* provides data on worker's occupation (ISCO-88) and years of education. Average years of education for first skill level (elementary occupations), second skill level (clerks, craft workers and plant and machine operators and assemblers), third skill level (technicians and associate professionals) and forth skill level (managers and professionals) are 7.8, 9.9, 13.7 and15.2 years, respectively.

Following Liu (1991), capital stock is constructed by the perpetual inventory method assuming a depreciation rate of 5 percent for building, 10 percent for machinery and 20 percent for vehicles. Both capital stock and investment are deflated by the deflator for the gross fixed capital formation. However, as the deflator for the gross fixed capital formation for the food processing industry is not available in the *Chilean National Account*, we use deflator for the whole manufacturing industry. Also, note that the deflator is only available at national level.

Therefore, we control for the regional and industrial difference in output prices and other unobservable regional and industrial heterogeneity with provincial and industrial dummies in the production function.

Endnotes

[1] The most common measure of skill intensity is the share of educated workers (high-school diploma, college degree or nonproduction workers) in total employment (Feenstra and Hanson 1997; Moretti 2004a).

[2] For analytical simplicity, we substituted $w_s / w_u = 1$ in deriving equation (1).

[3] In the Chilean case, there are 51 provinces and 342 counties (regions).

[4] For details on bootstrapping procedures, refer to Levinsohn and Petrin (2003).

[5] See Appendix A for the derivation of the third line of equation (20), which does not include subscripts for ease of exposition.

[6] Refer to Liu (1991) and Appendix B for details on the construction of plant-level variables.

[7] We use the distance-weighted average years of education in a county, the distance-weighted average years of education within a macro-region in a county and the average years of education in a county as an instrument for S_{SKL1}, S_{SKL2} and S_{SKL3}, respectively.

[8] The critical value is 16.38 for 10 percent from Stock and Yogo (2005).

[9] We use the 90th percentile value instead of the maximum value to avoid misrepresenting change in variables caused by outliers.