Capital-Skill Complementarity: Does capital composition matter?*

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Abstract

Using panel data from Chilean manufacturing plants, we study the existence of capital-skill complementarity in a developing country. We also study whether the composition of capital matters. We disaggregate the stock of capital in different types according to their technological content. We find: (1) the elasticity of substitution between capital and skilled labor is lower than the elasticity of substitution between capital and unskilled labor, and (2) the higher the technological component of the capital stock the larger the size of complementarity between capital and skilled labor. Our findings show that capital, as an aggregate input, may under(over) state the complementarity between labor and the type of capital these workers actually use.

Keywords: capital-skill complementarity, technological capital, translog function
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I. Introduction

The stock of capital may substitute or complement labor depending the type of labor used in the production process. Griliches (1969) posits that capital is less substitutable

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for skilled labor than for unskilled labor (capital-skill complementarity). Therefore, as stated by Krusell et al. (2000), in a framework where capital and unskilled labor are perfect substitutes, and they have unit elasticity of substitution with skilled labor, capital accumulation increases the marginal product of skilled labor and decreases the marginal product of unskilled labor, increasing the skill wage premium. Since Griliches (1969) first stated his hypothesis, several studies have attempted to test it. Although some of the literature on this topic supports the Griliches (1969) hypothesis, the evidence has been almost exclusively concentrated in developed countries.

Additionally, most of the related articles regard capital as an aggregate input and do not consider that there are also differences in the complexity of capital. Is the elasticity of substitution between software (technological capital) and skilled labor lower than the elasticity of substitution between software and unskilled labor? Is the elasticity of substitution between a truck (non-technological capital) and skilled labor significantly different from the elasticity of substitution between a truck and unskilled labor? Most of the studies have omitted this issue and thus, whenever capital accumulation is accompanied with a change in the composition of capital, these studies may under(over)state the complementarity between skilled labor and the type of capital that these workers actually use.

This paper presents an input function model with skilled labor, unskilled labor, technological capital, and non-technological capital as production factors. Using panel data from Chilean manufacturing plants, we disaggregate the stock of capital, defining three different specifications for the technological stock of capital. We find that the elasticity of substitution between capital and skilled labor is lower than the elasticity of substitution between capital and unskilled labor, supporting the Griliches (1969) hypothesis in a developing country.

We also find that the higher the technological component of the capital stock the larger the size of complementarity between capital and skilled labor. Our result suggests that as the composition of the stock of capital moves toward more technological capital, the expected rise in the skill premium might be higher. This issue has generally been overlooked by the existing literature. However, our finding is important since this literature may understate the impact of capital-skill complementarity on the skill premium in countries where the accumulation of technological capital is increasing rapidly. Indeed, Bruno et al. (2009) show that developing countries accumulate physical capital first and then they begin to import technological capital in a second stage of development.

Additionally, in most of our specifications, the elasticity of substitution between non-technological capital and skilled labor is larger than the elasticity of substitution between technological capital and unskilled labor; e.g., a machine can more easily substitute for skilled workers than can software for unskilled workers. We denote this result as the *compensation effect*, since it abates the unskilled labor demand decrease produced by the capital accumulation when capital-skill complementarity holds.

Although it is more intuitive to expect that software is more substitutable for unskilled workers than a machine is for skilled workers, our result can be explained by the idea that the productivity gap between skilled and unskilled workers using non-technological capital might not be large. For instance, skilled workers are not much more productive than unskilled workers when driving trucks or operating a machine that performs routine tasks. Therefore, the elasticity of substitution between non-technological capital and skilled labor is smaller but close to the elasticity of substitution between non-technological capital and unskilled labor. This phenomenon, combined with the fact that non-technological capital substitutes for more workers than technological capital does (since machines can usually replace a large number of unskilled workers in some industrial processes), explains why the compensation effect is observed in the data. This effect is stronger when we consider more high-tech definitions of technological capital. The reason behind this result is that the elasticity of substitution between technological capital and unskilled labor strongly decreases as soon as technological capital becomes more high-tech.

A. Related literature

Capital-skill complementarity has been extensively analyzed for developed countries.[1] Nevertheless, there have been very few attempts, such as Yasar and Paul (2008) and Akay and Yuksel (2009), to verify whether the capital-skill complementarity hypothesis holds for developing countries.

The evidence does not strongly support the capital-skill complementarity hypothesis. Duffy et al. (2004), using a panel of countries, find weak evidence of capital-skill complementarity. However, in some of their specifications, they find that capital-skill complementarity is more significant with lower thresholds for the definition of skilled labor.[2]

Papageorgiou and Chmelarova (2005) find no evidence of capital-skill complementarity in OECD countries. They state that capital-skill complementarity is relatively more pronounced in countries with an initial medium income and a low literacy rate. They use school attainment to construct the skilled and unskilled labor variables.

However, Krusell et al. (2000) find that the elasticity of substitution between capital equipment and unskilled labor is higher than the elasticity of substitution between capital equipment and skilled labor. Using U.S. time series between 1963 and 1992,[3] they find positive elasticity of substitution between capital equipment and labor for both skilled and unskilled labor; however, the estimated elasticity of substitution between capital

[1] See, for instance, Bergstrom and Panas (1992) and Krusell et al. (2000).

[2] Duffy et al. (2004) work with five thresholds to define skilled labor: (1) "workers who have attained some postsecondary education," (2) "workers who have completed secondary education," (3) "workers who have attained some secondary education," (4) "workers who have completed primary education," and (5) "workers who have attained some primary education."

[3] Krusell et al. (2000) construct the stock of capital using Gordon (1990) data.

and unskilled labor is around 2.5 times that of capital and skilled labor. These results, though, have been criticized by Polgreen and Silos (2008), who state that the elasticity of substitution between capital equipment and unskilled labor is understated, as Krusell et al. (2000) use a capital growth that "implies very rapid growth in the stock of capital equipment."

Bartel et al. (2007) posit that IT machines require operators with engineering, programming, and problem-solving skills. Therefore, technological capital is related more to specific skills than to school attainment. This point is consistent with Krueger (1993) and Autor et al. (2006), who find that computerization has increased the wages of workers who perform non-routine tasks relative to the wages of workers whose jobs involve routine tasks.[4]

Goldin and Katz (1998) argue that capital-skill complementarity may hold for some industries but not for others. Bergstrom and Panas (1992), using a panel of Swedish manufacturing industries, find that capital-skill complementarity holds most of the time. However, the size of capital-skill complementarity that they find is different across industries.

The lack of strong evidence of capital-skill complementarity has been taken as an argument to sustain that most of the increase in the skill premium in developed countries is explained by skill biased technological change, as stated by Berman et al. (1994), Ruiz-Arranz (2003), Balleer and van Rens (2013), among others. However, as shown by Krugman (1979), Acemoglu and Zilibotti (2001), Tanaka (2006), among others, new technologies are usually flourished in developed countries while most of developing countries adopt new technologies via capital accumulation. Therefore, the evidence of capital-skill complementarity seems to be a strong candidate to explain why the wage skill premium has risen in some of these countries, as shown by Parro (2013).

However, data sets from developing economies lack of information on disaggregated measures of capital; e.g., software and computers. Akay and Yuksel (2009), for instance, define machines, tools, and other equipment as capital stock. Using panel data from Ghanaian manufacturing firms, they find that the elasticity of substitution between capital and unskilled labor is slightly higher than the elasticity of substitution between capital and skilled labor. This evidence of capital-skill complementarity in Ghana is weaker than that found by Krusell et al. (2000).

If we take into account non-technological capital only, our findings show a similar result to that found by Akay and Yuksel (2009).[5] However, when we consider technological capital, our results suggest strong evidence of capital-skill complementarity, supporting

[4] Krueger (1993) finds that workers who use computers earn 10% to 15% higher wages than those who do not use computers.

[5] Akay and Yuksel (2009) find the ratio of the substitution elasticity of capital and unskilled labor to that of capital and skilled labor to be 1.1, while Krusell et al. (2000) find this ratio to be 2.5. In our results, the ratio is 1.1.

the idea that the composition of capital matters. We even find that technological capital and skilled labor are complements in some specifications.

The existence of capital-skill complementarity has also been studied in international trade literature. Traditional trade theories predict that as economies open to international trade, developed countries will specialize in the production of goods that are intensive in skilled labor, while developing countries will produce goods that are intensive in unskilled labor. This prediction implies that the relative wage of skilled workers should increase in developed countries but decrease in developing countries as economies open to international trade.

However, the opposite phenomenon is observed in the data. As documented by Parro (2013), the skill premium has increased in several developing countries. Gallego (2011) shows that the rise in the skill premium has also been present in the Chilean labor market. The latter contradicts the main prediction of the standard Heckscher-Ohlin model of trade.

Nevertheless, when capital-skill complementarity exists, there is an additional force balancing the effect of the Stolper-Samuelson theorem. Trade openness may stimulate investment in a developing country that opens its economy, since an important portion of equipment in that country must be imported rather than be produced by the country's own technology (e.g., computers). Therefore, if the capital-skill complementarity hypothesis holds, trade openness may increase the relative demand for more educated workers and push the skill premium up in those economies. For instance, Parro (2013) shows evidence that the introduction of trade in capital goods, together with capital-skill complementarity, generates a skill-biased trade effect and thus allows the possibility of an important positive effect on the skill premium.

The rest of the paper is organized as follows. Section II. explains how the compensation and augmenting effects in a capital-skill complementarity framework of two types of capital. Section III. describes the data that we are working with. Section IV. presents the empirical strategy. Section V. shows our results, supporting the evidence of capital-skill complementarity and the compensation effect in most of our specifications. Section VI. concludes.

II. Capital-Skill Complementarity with Two Types of Capital

We assume an input function $F(L, S, T, K)$, where L denotes the working hours of unskilled workers, S the working hours of skilled workers, T technological capital, and K non-technological capital. We first express the elasticity of substitution between input i and input j as σ_{ij}. Then, we define relative capital-skill complementarity as $\sigma_{zL} > \sigma_{zS}$ and absolute capital-skill complementarity as $\sigma_{zL} > 0 > \sigma_{zS}$, $\forall z \in \{K, T\}$.

When disaggregating capital, we can also check the order of the elasticity of substitution between non-technological capital and skilled labor (σ_{KS}), and the elasticity of substitution between technological capital and unskilled labor (σ_{TL}). We define compensation effect (augmenting effect) whenever $\sigma_{KS} > \sigma_{TL}$ ($\sigma_{KS} < \sigma_{TL}$), thus we can argue that non-technological capital is more (less) substitutable for skilled workers than technological capital is for unskilled workers.

Whenever capital-skill complementarity holds, we know that $\sigma_{KL} > \sigma_{KS}$ and $\sigma_{TL} > \sigma_{TS}$. As we can see in figure 1, $\sigma_{TS} > \sigma_{KL}$ is sufficient condition (but not necessary as we will see in the next paragraph) for the augmenting effect to hold. Since $\sigma_{KL} > \sigma_{KS}$ and $\sigma_{TL} > \sigma_{TS}$, whenever $\sigma_{TS} > \sigma_{KL}$ the value projected by σ_{TL} in point B is always larger than the value projected by σ_{KS} in point A.

However, whenever capital-skill complementarity holds and $\sigma_{TS} < \sigma_{KL}$, both effects are possible. We can first notice from figure 2 that the value projected by σ_{TL} in point B is larger than the value projected by σ_{KS} in point A and thus the augmenting effect holds in such a case. However, as we can see in figure 3, the value projected by σ_{KS} in point A is larger than the value projected by σ_{TL} in point B and hence the compensation effect holds. Therefore, whenever capital-skill complementarity holds and $\sigma_{TS} < \sigma_{KL}$ the order between σ_{TL} and σ_{KS} is ambiguous. In this case, whether we have the compensation effect or the augmenting effect depends on the distance between σ_{TS} and σ_{KL}, and the size of capital-skill complementarity.

Since $\sigma_{TS} > \sigma_{KL}$ means that, for instance, software is more substitutable for skilled workers than machines are for unskilled workers (a case very unlikely to occur), without loss of generality, our analysis focuses on the assumption that $\sigma_{TS} < \sigma_{KL}$. Figure 4 shows isoquants of the four different input relations that we are interested in. Vertical axes denote the type of capital, while horizontal axes denote the type of labor. By capital-skill complementarity, we know that $\sigma_{KL} > \sigma_{KS}$ and $\sigma_{TL} > \sigma_{TS}$. The latter is the reason why the isoquant in subfigure 4b (subfigure 4d) is more L-shaped than the isoquant in subfigure 4a (subfigure 4c). From $\hat{\sigma}_{TS} < \hat{\sigma}_{KL}$, we also know that the isoquant in subfigure 4d is more L-shaped than the isoquant in subfigure 4a. What we do not know is whether the isoquant in subfigure 4b is more or less L-shaped than the isoquant in subfigure 4c.

Therefore, figure 4 indicates that the augmenting effect (compensation effect) holds whenever the isoquant in subfigure 4b is more (less) L-shaped than the isoquant in subfigure 4c. We can notice that there is a combination of two factors driving either the augmenting or compensation effect: the user-friendliness of the type of capital, which determines the level of capital-skill complementarity, i.e., $|\sigma_{KL} - \sigma_{KS}|$ and $|\sigma_{TL} - \sigma_{TS}|$; and the level of substitution of non-technological capital for unskilled labor compared to the level of substitution of technological capital for skilled labor, i.e., $|\sigma_{KL} - \sigma_{TS}|$.

It is reasonable to assume that a user-friendly machine would be used by a lower ratio of skilled to unskilled workers than a very complex machine. Therefore, the more user-friendly the capital input, the smaller the degree of capital-skill complementarity, i.e., $\sigma_{KL} \approx \sigma_{KS}$ and $\sigma_{TL} \approx \sigma_{TS}$. If a process uses user-friendly machines, but these machines can perform tasks that would otherwise be performed by a large number of workers, assuming that skilled workers are more scarce than unskilled ones, we expect the compensation effect to hold. However, if machines are complex to use, we expect that the size of capital-skill complementarity is large, thus as long as the distance between σ_{KL} and σ_{TS} is small the augmenting effect is more likely to hold.

III. Data and Variables

To perform the empirical analysis, we use the Annual Chilean Survey of Manufacturers (ENIA) panel data from 2000 to 2011. Conducted by the Chilean Institute of Statistics, the ENIA is an annual census of manufacturing plants with 10 or more employees. ENIA data have been used in many relevant studies, such as Tybout et al. (1991), Liu (1993), Levinsohn (1999), Pavcnik (2002), and Levinsohn and Petrin (2003), among others.

The ENIA 2000-2011 provides us with comprehensive data of the Chilean manufacturing sector. We focus our analysis on the plants that are linked to a particular industry.[6] Thus, we include plants operating in 52 industries identified by the International Standard Industrial Classification (ISIC) at the three-digit level.[7]

The data retrieved from the ENIA 2000-2011 include gross fixed assets by type of asset, investment in fixed assets by type of asset, labor hours by type of labor, labor compensation by type of labor, value added, financial cost, corporate taxes and ISIC code.

The ENIA provides the previous year's value and the current year's investment in eight types of fixed assets: land, buildings, machinery and equipment, furniture and fixtures, vehicles, software, other tangible fixed assets, and other intangible assets.[8] However, separate information for "software" and "other intangible assets" is available since 2008. Software and other intangible assets are included in "machinery and equipment" before 2008. We deflate each type of fixed asset by the fixed asset deflator provided by the Central Bank of Chile.

Using the perpetual inventory method, we can therefore compute the capital stock for each type of asset as

$$k_{it} = (1 - \delta_k)k_{it-1} + I_{it},$$

where k_{it} is the deflated type of fixed asset for plant i at time t, δ_k denotes the depreciation

[6] We do not include plants without an ISIC industry classification or plants with negative values of T and/or K, which occurs when plants sell their fixed assets (negative investment) and the last-period capital stock discounted by depreciation is not large enough to compensate for the negative investment.

[7] Table 1 shows the industries of our data, at the ISIC-2 level. We use the classifications provided by the third revision of the ISIC.

[8] "Other tangible fixed assets" include tools and IT equipment, while "other intangible assets" include patents, trademarks, goodwill, and water use permits.

rate of fixed asset k,[9] and I is the investment in fixed asset k.[10]

We calculate the aggregate rental cost of capital r as

$$r = \frac{B + \delta}{1 - \tau},$$

with B as the discount rate and τ the effective corporate tax rate.[11]

In order to define both technological capital T and non-technological capital K, we build three different specifications. In Specification 1, we define T as software and K as the rest of fixed assets. In Specification 2, we define T as software plus intangible assets. Finally, in Specification 3, we define T as the sum of software, other intangible assets, machinery and equipment, and other tangible fixed assets.

The ENIA contains detailed information on both labor hours and labor compensation for non-specialized personnel, maintenance workers, clerks, personal service workers, specialized workers, administrative personnel, and managers. We define specialized workers, administrative personnel, and managers as skilled workers S, and the rest of the categories as unskilled workers L. As a crude robustness check of our definition of skilled and unskilled workers, we computed the average percentage of skilled hours over the total hours in the data set. Around 23% of the total hours corresponds to skilled labor. This number is roughly close to the fraction of workers who complete a college education in Chile.

IV. Empirical Strategy

In order to answer our main question, we have to estimate the elasticities of substitution between the different labor and capital categories.

As we can notice from our database, we observe input real values but not input prices. Therefore, as in section II., we assume an input function $F(L, S, T, K)$, where L denotes the working hours of unskilled workers, S the working hours of skilled workers, T technological capital, and K non-technological capital. Following Berndt and Christensen (1973) and Berndt and Christensen (1974), we assume that we can characterize the input

[9] We use a depreciation rate of 2.5%, 13%, 25%, 13%, and 31.5% for buildings, machinery and equipment, vehicles, intangible assets, and software, respectively, as documented by Oulton and Srinivasan (2003). We use a depreciation rate of 18% for other tangible fixed assets, as reported by the U.S. Bureau of Economic Analysis.

[10] Investment is defined as the purchase of new and used assets plus asset improvements minus the sales of used assets.

[11] The depreciation rate δ used in this formula is the weighted average of the fixed assets' depreciation rates. We follow Cerda and Saravia (2009) to compute the discount rate B and the effective corporate tax rate τ, where B is the weighted average of the ratio of financial cost to value added and τ is the weighted average of the ratio of effective tax paid to value added.

function in a translog form as[12]

$$\begin{aligned}\ln F &= \beta_0 + \beta_L \ln L + \beta_S \ln S + \beta_T \ln T + \beta_K \ln K + \frac{1}{2}\gamma_{LL}(\ln L)^2 + \gamma_{LS} \ln L \ln S \\ &\quad + \gamma_{LT} \ln L \ln T + \gamma_{LK} \ln L \ln K + \frac{1}{2}\gamma_{SS}(\ln S)^2 + \gamma_{ST} \ln S \ln T + \gamma_{SK} \ln S \ln K \\ &\quad + \frac{1}{2}\gamma_{TT}(\ln T)^2 + \gamma_{TK} \ln T \ln K + \frac{1}{2}\gamma_{KK}(\ln K)^2.\end{aligned}$$

Since we do not observe input prices, we assume that input markets are competitive. Considering this assumption we can now state that $\frac{\partial F}{\partial L} = P_L$, $\frac{\partial F}{\partial S} = P_S$, $\frac{\partial F}{\partial T} = P_T$, and $\frac{\partial F}{\partial K} = P_K$, where P_i denotes the price of input i relative to the price of the aggregate input function F. Knowing that $\frac{\partial \ln F}{\partial \ln i} = \frac{P_i i}{F}$, the cost share of input i (s_i), we have

$$\begin{aligned} s_L &= \beta_L + \gamma_{LL} \ln L + \gamma_{LS} \ln S + \gamma_{LT} \ln T + \gamma_{LK} \ln K, \\ s_S &= \beta_S + \gamma_{LS} \ln L + \gamma_{SS} \ln S + \gamma_{ST} \ln T + \gamma_{SK} \ln K, \\ s_T &= \beta_T + \gamma_{LT} \ln L + \gamma_{ST} \ln S + \gamma_{TT} \ln T + \gamma_{TK} \ln K, \\ s_K &= \beta_K + \gamma_{LK} \ln L + \gamma_{SK} \ln S + \gamma_{TK} \ln T + \gamma_{KK} \ln K. \end{aligned} \tag{1}$$

Since the cost shares must sum up to 1, we assume the additional restrictions that $\gamma_{ij} = \gamma_{ji}$ and $\sum_j \gamma_{ij} = 0$, with $j \in \{L, S, T, K\}$. Imposing these restrictions, dividing the inputs by K, and therefore dropping the last row and column of (1), we have the factor shares used in the estimation given by

$$\begin{aligned} s_L &= \beta_L + \gamma_{LL} \ln \frac{L}{K} + \gamma_{LS} \ln \frac{S}{K} + \gamma_{LT} \ln \frac{T}{K}, \\ s_S &= \beta_S + \gamma_{LS} \ln \frac{L}{K} + \gamma_{SS} \ln \frac{S}{K} + \gamma_{ST} \ln \frac{T}{K}, \\ s_T &= \beta_T + \gamma_{LT} \ln \frac{L}{K} + \gamma_{ST} \ln \frac{S}{K} + \gamma_{TT} \ln \frac{T}{K}. \end{aligned} \tag{2}$$

We assume that any deviation of the cost shares from the logarithmic marginal products is the result of errors in optimizing behavior. Therefore, we specify a classical additive disturbance for each of the equations in (2). Defining

$$y_i^{'} = \begin{bmatrix} s_L & s_S & s_T \end{bmatrix},$$

[12] As it can be seen, our input function is very similar to the Hicks-neutral constant returns to scale translog function proposed by Berndt and Christensen (1974).

$$\beta' = \begin{bmatrix} \beta_L & \gamma_{LL} & \gamma_{LS} & \gamma_{LT} & \beta_S & \gamma_{SS} & \gamma_{ST} & \beta_T & \gamma_{TT} \end{bmatrix},$$

and

$$X_i = \begin{bmatrix} 1 & \ln\frac{L}{K} & \ln\frac{S}{K} & \ln\frac{T}{K} & 0 & 0 & 0 & 0 & 0 \\ 0 & 0 & \ln\frac{L}{K} & 0 & 1 & \ln\frac{S}{K} & \ln\frac{T}{K} & 0 & 0 \\ 0 & 0 & 0 & \ln\frac{L}{K} & 0 & 0 & \ln\frac{S}{K} & 1 & \ln\frac{T}{K} \end{bmatrix}.$$

We can estimate $\hat{\beta}$ by Feasible Generalized Least Squares (FGLS) as

$$\hat{\beta} = (X'(\hat{\Omega} \otimes I_N)^{-1}X)^{-1}X'(\hat{\Omega} \otimes I)^{-1}y, \tag{3}$$

with Ω as the variance-covariance matrix and I an identity matrix. We also include fixed effects to control for fixed unobserved heterogeneity which might be correlated with the inputs and year effects to control for yearly shocks which might have affected the manufacturing sector, such as technology shocks.

In order to construct estimate $\hat{\beta}$, we first perform an OLS estimation of (2) to obtain each $\hat{s}_i$ and their respective residuals. We then construct the variance-covariance matrix $\hat{\Omega}$ of the residuals and take the Kronecker product of Ω and an identity matrix. After that, we compute $\hat{\beta}$, determined by equation (3).

As well as in Berndt and Christensen (1973) and Berndt and Christensen (1974), we use Allen-Uzawa elasticities of substitution to perform our analysis. Since we know that Allen-Uzawa elasticities are defined as

$$\hat{\sigma}_{ij} = \frac{\hat{\gamma_{ij}} + \hat{s}_i\hat{s}_j}{\hat{s}_i\hat{s}_j}, \tag{4}$$

$$\hat{\sigma}_{ii} = \frac{\hat{\gamma_{ii}} + \hat{s}_i^{\,2} - \hat{s}_i}{\hat{s}_i^{\,2}},$$

we use $\hat{\beta}$ to estimate $\hat{s}_i$ and insert them in equation (4) to obtain the Allen-Uzawa elasticities of substitution $\hat{\sigma}_{ij}$. Finally, we compute 95% confidence intervals for $\hat{\sigma}_{ij}$ using the bootstrap method.[13] All tables include results from both the estimation with fixed and year effects (Fixed Effects), and without fixed and year effects (Pooled).

V. Empirical Results

We first test capital-skill complementarity considering the aggregate level of capital; i.e., without distinguishing between technological and non-technological capital. Defining

[13]We perform the nonparametric bootstrap method (resampling with replacement) with 1,000 replications.

$Z = T + K$, as we can see in Table 3, the elasticity of substitution between aggregate capital and skilled labor ($\hat{\sigma}_{ZS}$) is lower than the elasticity of substitution between aggregate capital and unskilled labor ($\hat{\sigma}_{ZL}$), denoting relative capital-skill complementarity.[14] This result constitutes novel empirical evidence of capital-skill complementarity for a developing economy. As discussed in section I., this result is interesting since some studies show that most developing countries have experienced a rise in the skill premium in recent decades.

We now compare the aggregate and disaggregate elasticities of substitution, using the three specifications described in section III. Table 5 shows the elasticities of substitution for the disaggregate specifications.[15] We can see that there is both technological and non-technological capital-skill complementarity for all specifications. However, as soon as we use more disaggregate definitions of technological capital, the size of technological capital-skill complementarity (defined as $|\hat{\sigma}_{TL} - \hat{\sigma}_{TS}|$) increases, while the size of non-technological capital-skill complementarity remains roughly the same. We can even see that there is absolute technological capital-skill complementarity in Specifications 1 and 2 for the pooled regressions, whereas technological and non-technological capital-skill complementarity are very similar in Specification 3.

Another interesting result, which can be analyzed from Table 5, is that the compensation effect holds in all specifications ($\hat{\sigma}_{KS} > \hat{\sigma}_{TL}$). We can also see that as soon as we consider a more aggregate definition of technological capital, the compensation effect decreases. As both $\hat{\sigma}_{KL}$ and $\hat{\sigma}_{KS}$ remain roughly similar in the three specifications, what drives this result is that as soon as we consider more aggregate definitions for technological capital, $\hat{\sigma}_{TS}$ increases faster than $\hat{\sigma}_{TL}$ does. Therefore, the elasticity of substitution between technological capital and skilled labor is relatively more sensitive to the technological level of capital. We can also notice that elasticities of substitution are less sensitive when including fixed effects, although the main conclusions remain the same.

VI. Conclusion

Using data from Chilean manufacturing plants, we find that the elasticity of substitution between capital and skilled labor is lower than the elasticity of substitution between capital and unskilled labor, supporting the Griliches (1969) capital-skill complementarity hypothesis in a developing country.

Additionally, we find that the technological capital-skill complementarity is significantly larger than the non-technological capital-skill complementarity, for different specifications of technological capital. That is, the higher the technological component of the capital stock the larger the size of complementarity between capital and skilled labor. Our

[14]Table 2 shows the coefficients of equation (2) for the aggregate specification.
[15]Table 4 shows the coefficients of equation (2) for the disaggregate specifications.

results show that related articles regarding capital as an aggregate input, and disregarding that there are also differences in the complexity of capital, may under(over)state the complementarity between skilled labor and the type of capital that these workers actually use.

Another interesting result from our estimations is that the elasticity of substitution between non-technological capital and skilled labor is larger than the elasticity of substitution between technological capital and unskilled labor. We call this phenomenon a compensation effect, since it compensates for the decrease in the unskilled labor demand when capital-skill complementarity holds. This finding may sound counterintuitive, as it suggests, for example, that software is less substitutable for unskilled workers than are machines for skilled workers. However, we show that the compensation effect may occur when the productivity of skilled workers using non-technological capital is higher but close to the productivity of unskilled workers using that kind of capital. This is indeed the intuitive case. For instance, the productivity gap between skilled and unskilled workers driving a car or operating machines that perform routine tasks should be relatively small. If this is accompanied by the fact that non-technological capital substitutes for many more unskilled workers than technological capital does for skilled workers, the compensation effect is likely to hold. We find that the compensation effect is stronger when the technology level of the capital stock increases. This phenomenon occurs because the elasticity of substitution between technological capital and unskilled labor strongly decreases as soon as technological machines become more high-tech.

An interesting extension of this paper is to find the mechanism of how imports affect the skill premium. Since the composition of capital matters, an increase in technological capital imports, *ceteris paribus*, may raise the relative demand of skilled workers. This issue has been overlooked by the literature so far and it may help us understand not only the evolution of the skill premium over time but also cross-sectional variations of the skill premium at some moment in time.

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A Figures and Tables

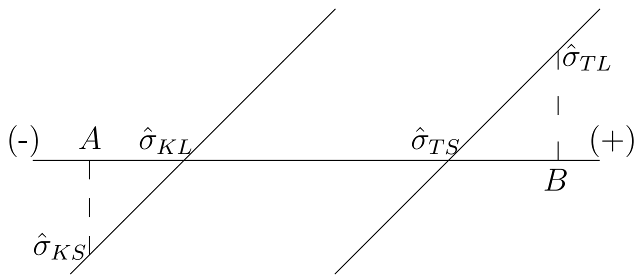


Figure 1: Augmenting effect when $\hat{\sigma}_{TS} > \hat{\sigma}_{KL}$

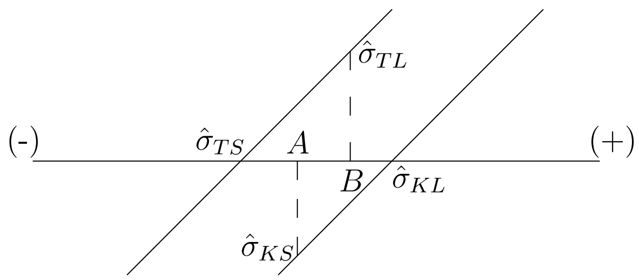


Figure 2: Ambiguous effect Case 1

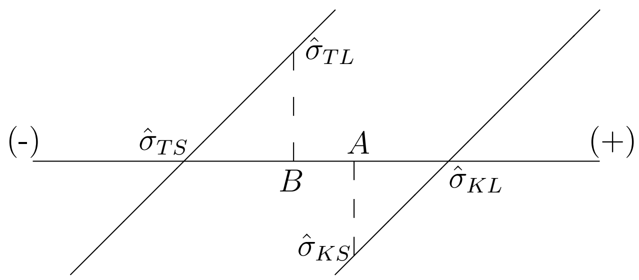
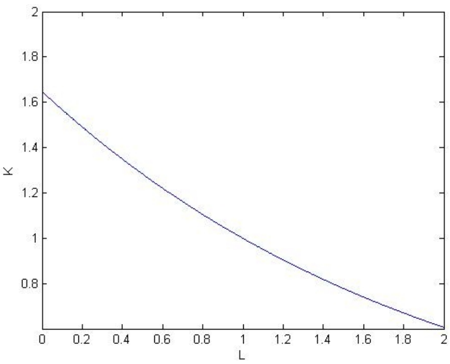
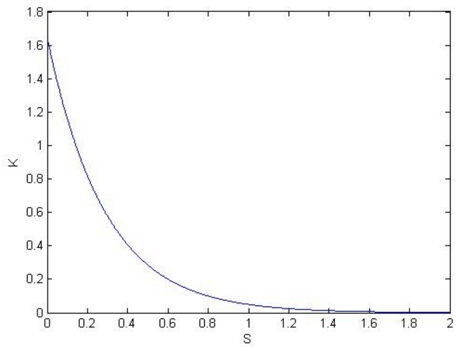


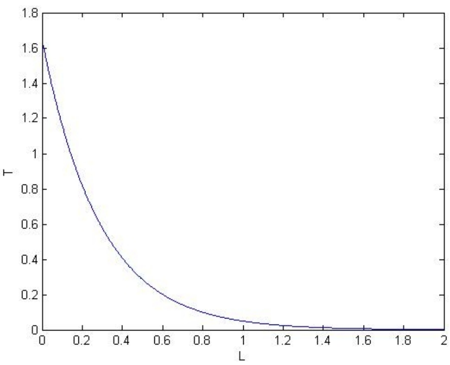
Figure 3: Ambiguous effect Case 2



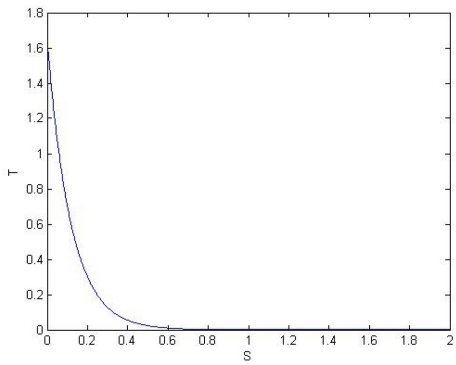
(a) Non-technological capital and unskilled labor



(b) Non-technological capital and skilled labor



(c) Technological capital and unskilled labor



(d) Technological capital and skilled labor

Figure 4: Capital and labor isoquants

Table 1: R&D Groups of Industries by ISIC Number

High	
24	Manufacture of chemicals and chemical products
29	Manufacture of machinery and equipment n.e.c.
30	Manufacture of office, accounting and computing machinery
31	Manufacture of electrical machinery and apparatus n.e.c.
32	Manufacture of radio, television and communication equipment and apparatus
33	Manufacture of medical, precision and optical instruments, watches and clocks
34	Manufacture of motor vehicles, trailers and semi-trailers
35 - 351	Manufacture of other transport equipment except building and repairing of ships and boats
Medium	
23	Manufacture of coke, refined petroleum products and nuclear fuel
25	Manufacture of rubber and plastics products
26	Manufacture of other non-metallic mineral products
27	Manufacture of basic metals
28	Manufacture of fabricated metal products, except machinery and equipment
351	Building and repairing of ships and boats
Low	
15	Manufacture of food products and beverages
16	Manufacture of tobacco products
17	Manufacture of textiles
18	Manufacture of wearing apparel; dressing and dyeing of fur
19	Tanning and dressing of leather; manufacture of luggage, handbags, saddlery, harness and footwear
20	Manufacture of wood and of products of wood and cork, except furniture; manufacture of articles of straw and plaiting materials
21	Manufacture of paper and paper products
22	Publishing, printing and reproduction of recorded media
36	Manufacture of furniture; manufacturing n.e.c.
37	Recycling

Table 2: Coefficients of Equation (2) for the Aggregate Specification

	Pooled		Fixed effects	
Variables	s_L	s_S	s_L	s_S
$Ln(L/Z)$	0.0665	-0.0395	0.0493	-0.0373
	(0.000346)***	(0.000257)***	(0.000329)***	(0.000267)***
$Ln(S/Z)$	-0.0395	0.0616	-0.0373	0.0470
	(0.000257)***	(0.000299)***	(0.000267)***	(0.000295)***
β	0.4630	0.3840	-0.0042	-0.0092
	(0.00269)***	(0.00249)***	(0.00156)***	(0.00149)***
Observations	33,003	33,003	33,003	33,003
R-squared	0.540	0.567	0.433	0.446

Standard errors in parentheses. ()*** Significant at the 1% level.

Table 3: Elasticities of Substitution for the Aggregate Specification

Elasticity	Pooled	Fixed effects
$\hat{\sigma}_{ZL}$	0.7578	0.8919
	[0.7501 0.7648]	[0.8855 0.8988]
$\hat{\sigma}_{ZS}$	0.6646	0.8530
	[0.6552 0.6733]	[0.8422 0.8636]
$\hat{\sigma}_{LS}$	0.7142	0.7305
	[0.7101 0.7183]	[0.7237 0.7367]
$\hat{\sigma}_{ZZ}$	-2.4185	-2.9342
	[-2.4553 -2.3826]	[-2.9753 -2.8938]
$\hat{\sigma}_{LL}$	-0.7827	-0.8561
	[-0.7939 -0.7720]	[-0.8681 -0.8454]
$\hat{\sigma}_{SS}$	-1.7433	-1.9225
	[-1.7687 -1.7173]	[-1.9485 -1.8931]
$\hat{\sigma}_{ZL}/\hat{\sigma}_{ZS}$	1.1402	1.0456

95% bootstrap confidence intervals in square brackets.

Table 4: Coefficients of Equation (2) for the Disaggregate Specifications

	Pooled			Fixed effects		
Specification 1	s_L	s_S	s_T	s_L	s_S	s_T
$Ln(L/K)$	0.0756	-0.0362	-0.000262	0.0544	-0.0375	-0.000145
	(0.000820)***	(0.000596)***	$(1.56e-05)$***	(0.000789)***	(0.000629)***	$(1.90e-05)$***
$Ln(S/K)$	-0.0362	0.0614	-0.000270	-0.0375	0.0503	-0.000147
	(0.000596)***	(0.000678)***	$(1.40e-05)$***	(0.000629)***	(0.000698)***	$(1.72e-05)$***
$Ln(T/K)$	-0.000262	-0.000270	0.000607	-0.000145	-0.000147	0.000656
	$(1.56e-05)$***	$(1.40e-05)$***	$(1.19e-05)$***	$(1.90e-05)$***	$(1.72e-05)$***	$(1.20e-05)$***
β	0.5180	0.3970	0.00615	0.0192	7.67e-05	-5.28e-05
	(0.00402)***	(0.00382)***	(0.000142)***	(0.00255)***	(0.00245)	$(5.18e-05)$
Observations	6,293	6,293	6,293	6,293	6,293	6,293
R-squared	0.575	0.559	0.277	0.449	0.457	0.320
Specification 2	s_L	s_S	s_T	s_L	s_S	s_T
$Ln(L/K)$	0.0756	-0.0361	-0.000434	0.0544	-0.0375	-0.000174
	(0.000822)***	(0.000597)***	$(5.97e-05)$***	(0.000789)***	(0.000629)***	$(6.35e-05)$***
$Ln(S/K)$	-0.0361	0.0615	-0.000531	-0.0375	0.0503	-0.000265
	(0.000597)***	(0.000679)***	$(5.35e-05)$***	(0.000629)***	(0.000699)***	$(5.77e-05)$***
$Ln(T/K)$	-0.000434	-0.000531	0.00133	-0.000174	-0.000265	0.00134
	$(5.97e-05)$***	$(5.35e-05)$***	$(4.56e-05)$***	$(6.35e-05)$***	$(5.77e-05)$***	$(3.99e-05)$***
β	0.5160	0.3940	0.0140	0.0191	6.02e-05	5.58e-05
	(0.00405)***	(0.00385)***	(0.000539)***	(0.00255)***	(0.00245)	(0.000176)
Observations	6,293	6,293	6,293	6,293	6,293	6,293
R-squared	0.574	0.559	0.113	0.449	0.456	0.149
Specification 3	s_L	s_S	s_T	s_L	s_S	s_T
$Ln(L/K)$	0.0734	-0.0389	-0.0247	0.0537	-0.0385	-0.0123
	(0.000821)***	(0.000606)***	(0.000486)***	(0.000803)***	(0.000652)***	(0.000481)***
$Ln(S/K)$	-0.0389	0.0609	-0.0156	-0.0385	0.0508	-0.0103
	(0.000606)***	(0.000681)***	(0.000425)***	(0.000652)***	(0.000717)***	(0.000428)***
$Ln(T/K)$	-0.0247	-0.0156	0.0436	-0.0123	-0.0103	0.0274
	(0.000486)***	(0.000425)***	(0.000609)***	(0.000481)***	(0.000428)***	(0.000701)***
β	0.4820	0.3780	0.0792	0.0189	0.0011	-0.0165
	(0.00398)***	(0.00372)***	(0.00243)***	(0.00263)***	(0.00252)	(0.00132)***
Observations	5,988	5,988	5,988	5,988	5,988	5,988
R-squared	0.574	0.568	0.466	0.444	0.458	0.213

Standard errors in parentheses. ()*** Significant at the 1% level.

Table 5: Elasticities of Substitution for the Disaggregate Specifications

	Pooled			Fixed effects		
Elasticity	Specification 1	Specification 2	Specification 3	Specification 1	Specification 2	Specification 3
$\hat{\sigma}_{KL}$	0.6430	0.6434	0.7396	0.8476	0.8480	0.9281
	[0.6175 0.6662]	[0.6181 0.6666]	[0.7213 0.7560]	[0.8275 0.8652]	[0.8279 0.8656]	[0.8854 0.9148]
$\hat{\sigma}_{KS}$	0.5722	0.5738	0.6936	0.7833	0.7852	0.9047
	[0.5469 0.5994]	[0.5484 0.6012]	[0.6775 0.7180]	[0.7540 0.8113]	[0.7559 0.8133]	[0.8639 0.9090]
$\hat{\sigma}_{TL}$	0.2349	0.3893	0.6187	0.5777	0.7547	0.8097
	[0.1247 0.3232]	[0.2530 0.5050]	[0.5723 0.6309]	[0.4668 0.6788]	[0.5953 0.8898]	[0.7625 0.8229]
$\hat{\sigma}_{TS}$	-0.4828	-0.4073	0.5445	0.1912	0.2978	0.6995
	[-0.6257 -0.3556]	[-0.5543 -0.2728]	[0.4732 0.5502]	[0.0112 0.3631]	[0.0261 0.5524]	[0.6022 0.7095]
$\hat{\sigma}_{KT}$	0.4735	-0.2384	0.6410	-1.5472	-2.0294	0.4831
	[0.2603 0.6856]	[-0.7039 0.2769]	[0.6059 0.7061]	[-1.8967 -1.1884]	[-2.6508 -1.3504]	[0.5531 0.6946]
$\hat{\sigma}_{LS}$	0.7409	0.7411	0.7324	0.7314	0.7310	0.7352
	[0.7309 0.7503]	[0.7311 0.7504]	[0.7123 0.7373]	[0.7155 0.7473]	[0.7151 0.7470]	[0.6814 0.7195]
$\hat{\sigma}_{KK}$	-2.2715	-2.2735	-8.8905	-3.0243	-3.0224	-10.6656
	[-2.3663 -2.1821]	[-2.3665 -2.1817]	[-2.7511 -2.5728]	[-3.1284 -2.9153]	[-3.1233 -2.9110]	[-3.3070 -3.1078]
$\hat{\sigma}_{TT}$	-135.2397	-27.2574	-4.2405	-26.0098	-24.8636	-5.3044
	[-198.5464 -60.7786]	[-89.9215 22.1521]	[-5.6931 -5.1908]	[-129.8683 98.3522]	[-77.8579 27.5946]	[-6.9426 -6.2617]
$\hat{\sigma}_{LL}$	-0.6619	-0.6627	-0.6409	-0.7425	-0.7436	-0.7128
	[-0.6848 -0.6393]	[-0.6859 -0.6398]	[-0.8933 -0.8353]	[-0.7652 -0.7219]	[-0.7668 -0.7231]	[-0.9976 -0.9411]
$\hat{\sigma}_{SS}$	-1.8440	-1.8439	-1.8104	-1.9935	-1.9945	-1.9413
	[-1.9027 -1.7808]	[-1.9032 -1.7813]	[-2.2722 -2.1138]	[-2.0590 -1.9296]	[-2.0605 -1.9309]	[-2.4559 -2.2937]
$\lvert\hat{\sigma}_{KL} - \hat{\sigma}_{KS}\rvert$	0.0708	0.0696	0.0460	0.0643	0.0628	0.0234
$\lvert\hat{\sigma}_{TL} - \hat{\sigma}_{TS}\rvert$	0.7177	0.7966	0.0742	0.3865	0.4569	0.1102
$\lvert\hat{\sigma}_{KS} - \hat{\sigma}_{TL}\rvert$	0.3373	0.1845	0.0749	0.2056	0.0305	0.0950
$\lvert\hat{\sigma}_{KL} - \hat{\sigma}_{TS}\rvert$	1.1258	1.0507	0.1951	0.6564	0.5502	0.2286

95% bootstrap confidence intervals in square brackets.