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Capital–Skill Complementarity: Does Capital Composition Matter?*

Juan A. Correa

Universidad Andres Bello, 7591538 Santiago, Chile
jlcorrea_allamand@yahoo.com

Miguel Lorca

University of New South Wales, NSW2052 Sydney, Australia
mlorcaes@gmail.com

Francisco Parro

Universidad Adolfo Ibáñez, 7941169 Santiago, Chile
fjparrog@gmail.com

Abstract

We estimate the effect of capital composition on the size of capital–skill complementarity and the skill wage premium. Disaggregating the capital stock into different types according to technological content, we find that: capital is more of a q-complement to skilled labor than to unskilled labor; the higher the technological component of capital, the larger the size of the relative q-complementarity between capital and skilled labor; and replacing non-technological with technological capital might increase the skill wage premium by about 9 percent. Our results highlight that changes in capital composition matter for understanding changes in the skill wage premium.

Keywords: Skill wage premium; technological capital; translog function

JEL classification: *D*24; *J*24; L60

I. Introduction

The stock of capital can substitute for or complement labor, depending on the type of labor used in the production process. Griliches (1969) posits that capital is less substitutable 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 have unit elasticity of substitution with skilled labor, capital accumulation

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increases the relative marginal product of skilled labor and pushes the skill wage premium up. Since Griliches (1969) first stated his hypothesis, several studies have attempted to test it. Although some studies in the body of literature on this topic support his hypothesis, the evidence has been almost exclusively concentrated in developed countries.

Moreover, most of the related articles regard capital as an aggregate input and do not consider that the technological composition of capital might matter. Does software (technological capital) substitute significantly more for unskilled workers than it does for skilled workers? Does a non-complex machine (non-technological capital) substitute for roughly the same number of unskilled and skilled workers? If the answer to these questions is yes, how does this phenomenon affect the skill wage premium?

In this paper, we use panel data from Chilean manufacturing plants to study these three questions. We present evidence on the existence of capital–skill complementarity, the effect of capital stock composition on the size of capital–skill complementarity, and the effect of capital composition on the skill wage premium. Our estimations also allow us to study the magnitude of the complementarity between non-technological capital and skilled labor, compared with the magnitude of the complementarity between technological capital and unskilled labor.

We build and estimate a four-input production function model with skilled labor, unskilled labor, technological capital, and non-technological capital as production factors. We disaggregate the stock of capital, defining two different specifications for the technological stock of capital. Following Sato and Koizumi (1973), Hamermesh (1985), and Stern (2011), we estimate the elasticities of complementarity for our four-input production function. We show that these elasticities allow us to establish a direct link between capital composition and the skill wage premium. We use the estimated elasticities of complementarity to quantify the effect of a change in the technological content of capital on the skill wage premium.

We find that capital is more of a q-complement to skilled workers than it is to unskilled workers, in line with the hypothesis of Griliches (1969). Moreover, we find that the higher the technological component of the capital stock, the larger the size of the relative q-complementarity between capital and skilled labor. We use the computed elasticities of complementarity to quantify the effect of capital composition on the skill wage premium. We show that as the composition of the stock of capital moves toward more technological capital, the skill wage premium rises. Moreover, our estimated elasticities imply that an economy replacing non-technological capital with technological capital, such that the contribution to output of technological capital increases by 50 percent while that of non-technological capital falls by the same magnitude, might experience an increase of about 9 percent in the skill wage premium, according to some of our estimations.[1]

Our results highlight the fact that not only the accumulation of aggregate capital but also changes in capital composition matter for understanding changes in the skill wage premium. This issue has generally been overlooked in the existing body of literature. However, our finding is important because previous studies might understate the impact of capital–skill complementarity on the skill wage 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 begin to import technological capital in a second stage of development.

Our paper is related to two strands of the literature. The first strand aims to build evidence on the capital–skill complementarity hypothesis. The second strand relates capital–skill complementarity to the rise in the skill wage premium in both developed and developing countries.

The first strand focuses on the partial elasticity of substitution and, thus, on the concepts of p-complementarity and p-substitution. If two types of inputs are p-complements, this elasticity is negative, and a decrease in the price of one input induces an increase in the employment of the other input. If these inputs are p-substitutes, the elasticity is positive and the opposite effect holds. Therefore, if the elasticity of substitution between capital and unskilled labor is higher than the elasticity of substitution between capital and skilled labor, a fall in the price of capital increases the relative demand for skilled workers, raising the skill wage premium.

Griliches (1969) posits that capital is less substitutable for skilled labor than for unskilled labor (capital–skill complementarity). Since he first established this hypothesis, capital–skill complementarity has been extensively analyzed for developed countries.[2] Nevertheless, there have been only very few attempts, such as those of 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.[3]

[1] Further details are given in Section II.

[2] See, for example, Bergstrom and Panas (1992) and Krusell *et al*. (2000).

[3] Duffy *et al*. (2004) work with five thresholds to define skilled labor: “workers who have attained some postsecondary education”; “workers who have completed secondary education”;

Papageorgiou and Chmelarova (2005) find no evidence of capital–skill complementarity in countries that belong to the Organisation for Economic Co-operation and Development (OECD). They state that capital–skill complementarity is relatively more pronounced in countries with an initial middle level of income and a low literacy rate. They use school attainment to construct the skilled and unskilled labor variables.

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 US time series between 1963 and 1992,[4] Krusell *et al*. (2000) find a positive elasticity of substitution between capital equipment and labor for both skilled and unskilled labor; however, the estimated elasticity of substitution between capital and unskilled labor is around 2.5 times that between capital and skilled labor. These results 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 deflator for nominal equipment stock 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.[5]

Goldin and Katz (1998) argue that capital–skill complementarity might 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 the capital–skill complementarity that they find differs across industries.

In our paper, we revisit the evidence of capital–skill complementarity for a developing country. We also assess whether the size of capital–skill complementarity depends on capital composition, specifically, the technological content of capital. Our analysis rests on the concept of q-complementarity (substitution) between inputs. The partial elasticity of complementarity ranges from negative infinite to positive infinite. If it is positive, the inputs are q-complements; if it is negative, they are

"workers who have attained some secondary education"; "workers who have completed primary education"; and "workers who have attained some primary education".

[4]They construct the stock of capital using data from Gordon (1990).

[5]Krueger (1993) finds that workers who use computers earn wages that are 10–15 percent higher than the wages of workers who do not.

q-substitutes. The elasticity of complementarity measures the effect of an increase in the quantity of one input on the price of the other input. Therefore, if the elasticity of complementarity between capital and skilled labor is higher than the elasticity of complementarity between capital and unskilled labor, a rise in the use of capital increases the relative wage of skilled workers. As a consequence of that, if technological capital is a stronger q-complement to skilled workers relative to unskilled workers than non-technological capital is, a change in the composition of capital, even holding the aggregate level of capital constant, raises the skill wage premium. We focus our analysis on the elasticities of complementarity because, as we show in Section II, these elasticities allow us to build a direct link between capital composition and the skill wage premium in our function.[6]

Our results are in line with the capital–skill complementarity hypothesis. We find that capital is a stronger q-complement to skilled labor than to unskilled labor. We also show that the higher the technological component of the capital stock, the larger the size of the relative q-complementarity[7] between capital and skilled labor. That is, the capital composition matters. Therefore, studies using aggregate capital might understate the size of the complementarity between capital and skilled labor.

Indeed, Akay and Yuksel (2009), using panel data from Ghanaian manufacturing firms, find that the elasticity of substitution between capital and unskilled labor is slightly higher than the elasticity of substitution between capital and skilled labor. If we take into account non-technological capital alone, our findings show a similar result to that found by Akay and Yuksel (2009).[8] However, when we consider technological capital, our results provide strong evidence of capital–skill complementarity, supporting the idea that the composition of capital matters.

The second strand of this literature links capital–skill complementarity with changes in the skill wage premium. Krusell *et al*. (2000) build an aggregate production function of four inputs (capital structures, capital equipment, unskilled labor, and skilled labor) and connect capital equipment–skill complementarity to the skill wage premium. The production function in Krusell *et al*. (2000) is a Cobb–Douglas function over

[6]In Appendix B, we derive a formal mathematical relationship between the partial elasticity of complementarity and the partial elasticity of substitution. Following this, we present estimates of the partial elasticities of substitution between different types of capital and skilled and unskilled labor.

[7]We define the concept of relative q-complementarity in Section II.

[8]Akay and Yuksel (2009) find the ratio of the elasticity of substitution between capital and unskilled labor to that between 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 similar to that of Akay and Yuksel (2009).

capital structures and a constant elasticity of substitution function of the three remaining inputs. That approach restricts the elasticity of substitution between capital structures and the nest of capital equipment, unskilled labor, and skilled labor to be equal to one. Moreover, it restricts the elasticity of substitution between unskilled labor and skilled labor to be the same as that between unskilled labor and equipment. Using this approach, Krusell *et al*. (2000) decompose the growth rate of the skill wage premium into three components: the growth rate of skilled labor input relative to the growth rate of unskilled labor input; the growth rate of skilled labor efficiency relative to that of unskilled labor efficiency; and the capital–skill complementarity effect. The last effect depends on the growth rate of equipment relative to the growth rate of skilled and unskilled labor input and the ratio of capital equipment relative to efficiency units of skilled labor, but not relative to the growth of capital structures.

Unlike that of Krusell *et al*. (2000), our approach allows us to analyze the skill wage premium when a change in capital composition occurs. Our approach does not restrict *ex ante* any of the self- and cross-elasticities of the four inputs included in the production function. The more flexible assumptions of our model allow us to analyze further interactions between inputs and the effect of capital composition on the skill wage premium. Krusell *et al*. (2000) omit any discussion regarding capital composition because their approach prevents them from deriving any flexible empirical relationship between capital composition and the skill wage premium.

The body of literature on international trade relates capital–skill complementarity to the rise of the skill wage premium in developing countries. 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 wage premium has increased in several developing countries. Gallego (2011) shows that the rise in the skill wage premium has also been present in the Chilean labor market. These findings contradict 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 might stimulate investment in a developing country that opens its economy, because an important portion of equipment in that country must be imported rather than produced by the country's own technology (e.g., computers). Therefore, if the capital–skill complementarity hypothesis holds, trade openness might increase the relative demand for more educated workers and push the skill wage premium up in those economies. 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 wage premium.

The lack of strong evidence of capital–skill complementarity has been taken as an argument for the claim 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), and Balleer and van Rens (2013), among others. However, as shown by Krugman (1979), Acemoglu and Zilibotti (2001), and Tanaka (2006), among others, new technologies usually flourish in developed countries, while most 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 skill wage premium has risen in some of these countries, as shown by Parro (2013). In this paper, we highlight that not only is the level of aggregate capital imports a relevant variable for understanding movements in the skill wage premium in developing economies, but so is the composition of imported capital, specifically, the technological content of capital.

The rest of the paper is organized as follows. In Section II, we discuss capital–skill complementarity and the skill wage premium in a framework with two types of capital. In Section III, we describe the data. In Section IV, we present the empirical strategy. In Section V, we discuss our estimation results and the impact of capital composition changes on the skill wage premium. Finally, we present our conclusions in Section VI.

II. Capital–Skill Complementarity and the Skill Wage Premium with Two Types of Capital

Consider a four-input production 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. In this section, we derive a relationship between changes in the technological content of capital and changes in the skill wage premium. We use the results derived in this section to quantify the effects of changes in capital composition on the skill wage premium, as shown in Section V.

The main tool in our analysis is the Hicks partial elasticity of complementarity, which ranges from negative infinite to positive infinite. If it is positive, the inputs are q-complements; if it is negative, they are q-substitutes. The partial elasticity of complementarity registers the effect on the price of one factor of a change in the quantity of another factor, holding marginal cost and quantities of other factors constant. The higher the elasticity of complementarity, the larger the positive effect of an increase in the quantity of one input on the price of the other input.[9]

Following Sato and Koizumi (1973), we define the partial elasticity of complementarity between input i and input j as $c_{ij} = FF_{ij}/F_iF_j$, $\forall i, j \in \{L, S, T, K\}$, where $F_i = \partial F/\partial i$ and $F_{ij} = \partial^2 F/\partial i \partial j$. We then define relative capital–skill q-complementarity as $c_{zS} > c_{zL}$, $\forall z \in \{K, T\}$. Thus, relative capital–skill q-complementarity compares the q-complementarity of c_{zS} and c_{zL}. When $c_{zS} > c_{zL}$, we say that inputs z and S are stronger q-complements than inputs z and L. In the following discussion, we simply use the term "capital–skill complementarity" when $c_{zS} > c_{zL}$.

When disaggregating capital, we assess how the magnitude of capital–skill complementarity changes with the technological content of capital stock. If $c_{TS} > c_{TL}$, $c_{KS} > c_{KL}$, and $c_{TS} - c_{TL} > c_{KS} - c_{KL}$, then capital–skill complementarity holds and the magnitude of the q-complementarity grows larger as the technological content of capital increases. For instance, knowing that $c_{TS} > c_{TL}$ and $c_{KS} > c_{KL}$, we can state that both a non-complex machine and software are more q-complementary to skilled labor. However, if $c_{TS} - c_{TL} > c_{KS} - c_{KL}$, the relative q-complementarity of software is larger. As we formally derive in the next subsection, under this condition, a change in the capital composition in favor of technological capital, T, raises the relative price of skilled labor, S (the skill wage premium).

This framework also allows us to estimate the order of the elasticity of complementarity between non-technological capital and skilled labor (c_{KS}) and the elasticity of complementarity between technological capital and unskilled labor (c_{TL}). Consider the case where capital–skill complementarity holds and, thus, $c_{KS} > c_{KL}$ and $c_{TS} > c_{TL}$. As we can see in Figure 1, $c_{KL} > c_{TS}$ is sufficient (but not necessary) for c_{KS} to be larger than c_{TL}. In that case, non-technological capital is more q-complementary to skilled workers than technological capital is to unskilled workers. However, whenever $c_{KL} < c_{TS}$, the ordering between c_{KS} and c_{TL} is ambiguous. Figure 2 shows that the value of c_{KS} can be larger than the value of c_{TL} under capital–skill complementarity. However, we observe in Figure 3 that the opposite conclusion can be reached under the same framework. Therefore, whether c_{KS} is larger or smaller than c_{TL} depends on the distance between c_{TS} and c_{KL} and the size of the capital–skill complementarity.

[9] Further discussion of this elasticity and its relation to elasticities of substitution can be found in Appendix B, as well as in Sato and Koizumi (1973), Hamermesh (1985), and Stern (2011).

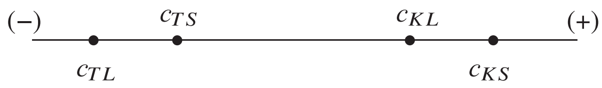

Fig. 1. $c_{TL} < c_{KS}$ when $c_{TS} < c_{KL}$

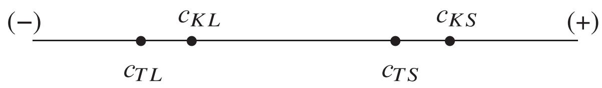

Fig. 2. Ambiguous effect, case 1

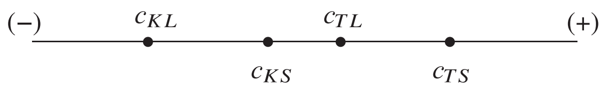

Fig. 3. Ambiguous effect, case 2

Capital–Skill Complementarity, Capital Composition, and the Skill Wage Premium

In this subsection, we analyze how changes in capital composition affect the skill wage premium, given the partial elasticities of complementarity. We call this the skill premium effect (SPE). Let the four-factor production function be $Y = F(L, S, T, K)$. The first-order conditions for the cost minimization are

$$P_i = \lambda F_i \quad \forall\ i \in \{L, S, T, K\}, \tag{1}$$

$$Y = F(L, S, T, K), \tag{2}$$

where λ is the Lagrange multiplier, which, in equilibrium, equals the marginal cost of production and $F_i = \partial F / \partial i$. Provided that the second-order conditions are satisfied, the first-order conditions described by equations (1) and (2) define the cost-minimizing input demand functions: $i = i(P_L, P_S, P_T, P_K, Y)$ $\forall i \in \{L, S, T, K\}$. Therefore, we can express the cost function as $C = G(P_L, P_S, P_T, P_K, Y)$, which is linear homogeneous and concave in prices.

Using Shepard's lemma, we can express the factor input demand functions as

$$i = G_i(P_L, P_S, P_T, P_K, Y) \quad \forall \quad i \in \{L, S, T, K\}, \tag{3}$$

where $G_i = \partial G / \partial i$.

We can perform the comparative statics of the factor input demand functions described by equation (3) and the equilibrium value of the Lagrange multiplier $\lambda = \lambda(P_L, P_S, P_K, P_T, Y)$, which is constant. Taking the total differential of these equations, we obtain

$$G_L dP_L + G_S dP_S + G_K dP_K + G_T dP_T = Y d\lambda,$$

$$G_i \frac{dY}{Y} + G_{iL} dP_L + G_{iS} dP_S + G_{iK} dP_K + G_{iT} dP_T = di,$$

where we have used the fact that $\partial\lambda/\partial Y = 0$ and $(\partial G_i/\partial Y)(Y/G_i) = 1$ because of the linear homogeneity of F and G.[10] In matrix form, we have

$$\begin{bmatrix} 0 & G_L & G_S & G_K & G_T \\ G_L & G_{LL} & G_{LS} & G_{LK} & G_{LT} \\ G_S & G_{SL} & G_{SS} & G_{SK} & G_{ST} \\ G_K & G_{KL} & G_{KS} & G_{KK} & G_{KT} \\ G_T & G_{TL} & G_{TS} & G_{TK} & G_{TT} \end{bmatrix} \begin{bmatrix} dY/Y \\ dP_L \\ dP_S \\ dP_K \\ dP_T \end{bmatrix} = \begin{bmatrix} Y d\lambda \\ dL \\ dS \\ dK \\ dT \end{bmatrix}.$$

Consider the effect on prices of a change in technological and non-technological capital, holding marginal cost and the quantities of inputs S and L constant. Denoting by H^G the bordered Hessian determinant of the cost function G and by H^G_{ij} the cofactor of G_{ij} in H^G, the effect on input i is

$$dP_i = \frac{H^G_{iT}}{H^G} dT + \frac{H^G_{iK}}{H^G} dK, \tag{4}$$

where H^G_{ij}/H^G is the element located in column i+1 and row j+1 of an inverse matrix of the bordered Hessian matrix of the cost function G.

Using the fact that the partial elasticity of complementarity is defined as $c_{ij} = (G/P_i P_j)(H^G_{ij}/H^G)$ in terms of the properties of the cost function (see Sato and Koizumi, 1973), we can express equation (4) as

$$\frac{dP_i}{P_i} = \left(s_T \frac{dT}{T}\right) c_{iT} + \left(s_K \frac{dK}{K}\right) c_{iK}, \tag{5}$$

where $s_j = P_j j/G$.[11]

[10]The translog production function satisfies the linear homogeneity property.

[11]Alternatively, we can arrive at an identical expression by exploiting the properties of the equilibrium condition in equation (1). The total differential of equation (1) produces $dP_i = d\lambda F_i + \lambda dF_i$. Then, the effect on prices of a change in technological and non-technological capital, holding marginal cost and the quantities of inputs S and L constant, is $dP_i = \lambda(F_{iT} dT + F_{iK} dK)$. Using equation (1) to solve for λ, and using the fact that $c_{ij} = F F_{ij}/F_i F_j$ in terms of the properties of the production function, we obtain the same expression as in equation (5) with $s_j = F_j j/F$.

Then, we can compute the SPE of a change in the stock of technological and non-technological capital as

$$\frac{dP_S}{P_S} - \frac{dP_L}{P_L} = \left(s_T \frac{dT}{T}\right)(c_{ST} - c_{LT}) + \left(s_K \frac{dK}{K}\right)(c_{SK} - c_{LK}). \tag{6}$$

Next, we define a change in capital composition. First, by differentiating the production function, holding the quantities of inputs S and L constant, we obtain

$$\left.\frac{dF}{F}\right|_{S=\overline{S}, L=\overline{L}} = s_T \frac{dT}{T} + s_K \frac{dK}{K}.$$

We consider a change in capital composition such that the change in output driven by a change in K is totally compensated by the change in output driven by the change in T; that is, $s_T(dT/T) = -s_K(dK/K)$. Plugging this condition into equation (6), we obtain

$$\text{SPE} = \left(s_T \frac{dT}{T}\right)[(c_{ST} - c_{LT}) - (c_{SK} - c_{LK})], \tag{7}$$

where $\widetilde{s}_T = s_T(dT/T)$ is the contribution to output of an increase in technological capital.

Therefore, whenever technological capital–skill complementarity is larger than non-technological capital–skill complementarity (i.e., $c_{TS} - c_{TL} > c_{KS} - c_{KL}$), a change in capital composition in favor of technological capital will have a positive effect on the skill wage premium.

III. Data and Variables

To perform the empirical analysis, we use panel data from the Annual Chilean Survey of Manufacturers (ENIA) from 2000 to 2011. Conducted by the Chilean Institute of Statistics, the ENIA is an annual census of manufacturing plants with ten 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).

The ENIA 2000–2011 provides us with comprehensive data on the Chilean manufacturing sector. We focus our analysis on the plants that are linked to a particular industry.[12] Thus, we include plants operating in 52

[12]We do not include plants without an ISIC 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.

industries identified by the International Standard Industrial Classification (ISIC) at the three-digit level.[13]

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 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.[14] However, separate information for "software" and "other intangible assets" has been available since 2008. Software and other intangible assets were 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 rate of fixed asset k,[15] and I is the investment in fixed asset k.[16]

We calculate a rental cost of capital for each type of capital r_z, $\forall z \in \{K, T\}$, as

$$r_z = \frac{B + \delta_z}{1 - \tau},$$

with B as the aggregate discount rate, δ_z as the depreciation rate for the type of capital z, and τ as the aggregate effective corporate tax rate.[17]

To define both technological capital T and non-technological capital K, we build two different specifications. In specification 1, we define T as

[13] We use the classifications provided by the third revision of the ISIC.

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

[15] We use depreciation rates of 2.5, 13, 25, 13, and 31.5 percent 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 percent for other tangible fixed assets, as reported by the US Bureau of Economic Analysis.

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

[17] The depreciation rate δ used in this formula is the weighted average of the fixed assets' depreciation rates described previously. 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.

software and K as the rest of fixed assets. In specification 2, 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, administrative personnel, specialized workers, and managers. We define specialized workers 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 dataset. Around 23 percent of the total hours corresponds to skilled labor. This number is roughly close to the percentage of workers who complete a college education in Chile. We also denote by SC the skilled labor compensation and LC the unskilled labor compensation.

To construct the input shares, we first define the technological capital compensation as $r_T T$ and the non-technological capital compensation as $r_K K$. Then, we denote by IC the total input cost defined as the sum of SC, LC, $r_T T$, and $r_K K$. Finally, we compute the skilled labor input share s_S as SC/IC, the unskilled labor input share s_L as LC/IC, the technological capital input share s_T as $r_T T/IC$, and the non-technological capital input share s_K as $r_K K/IC$.

IV. Empirical Strategy

In this section, we present and discuss our empirical framework. In our database, we observe input real values but not input prices. Therefore, we assume that in the overall production function there exists a four-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 assume that this four-input function is weakly separable from all other inputs[18] and exhibits constant returns to scale. We also assume that any technical change affecting L, S, T, and K is Hicks-neutral. These assumptions are sufficient to allow us to analyze the complementarity (substitution) possibilities between L, S, T, and K regardless of the level of other inputs or the level of technology. Following Berndt and Christensen (1973a, 1974), we assume that the input function F can be represented by the translog form

[18]Berndt and Christensen (1973a,b) provide a complete and rigorous demonstration of the conditions for weak and strong input separability.

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

Assuming competitive markets, a necessary condition for profit maximization is $\partial F/\partial i = P_i$, where P_i denotes the price of input $i \in \{L, S, T, K\}$, relative to the price of the aggregate input function F. This implies the equivalent condition $\partial \ln F/\partial \ln i = (\partial F/\partial i)(i/F) = P_i i/F = s_i$, where s_i is the cost share of input i in the total cost of producing F. Taking the partial derivative of function F with respect to each input and equating them to the cost shares, we have

$$
\begin{aligned}
s_L &= \beta_L + \gamma_{LL} \ln L + \gamma_{LS} \ln S + \gamma_{LT} \ln T + \gamma_{LK} \ln K, \\
s_S &= \beta_S + \gamma_{LS} \ln L + \gamma_{SS} \ln S + \gamma_{ST} \ln T + \gamma_{SK} \ln K, \\
s_T &= \beta_T + \gamma_{LT} \ln L + \gamma_{ST} \ln S + \gamma_{TT} \ln T + \gamma_{TK} \ln K, \\
s_K &= \beta_K + \gamma_{LK} \ln L + \gamma_{SK} \ln S + \gamma_{TK} \ln T + \gamma_{KK} \ln K. \qquad (8)
\end{aligned}
$$

We have assumed that our function F exhibits constant returns to scale. If equation (8) is subject to constant returns to scale, the following restrictions hold: $\sum_i \beta_i = 1$ and $\sum_i \gamma_{ij} = \sum_j \gamma_{ji} = \sum_i \sum_j \gamma_{ij} = 0$, with $j \in \{L, S, T, K\}$. Therefore, constant returns to scale together with competitive markets ensure that the sum of the cost shares exhausts total cost. Moreover, a symmetric condition is necessary for the applicability of Young's theorem to integrable functions. Symmetry restrictions imply that $\gamma_{ij} = \gamma_{ji}$.[19]

The assumption of linear homogeneity of F, together with the symmetry restrictions, ensures that the parameter estimates of any three equations of equation (8) will identify exactly all parameters of the input function. Imposing these restrictions on the system of equations (8), dividing inputs by K, and therefore dropping the last row and column of equation (8), we have the factor shares used in the estimation given by

[19]Such equality might, in principle, be tested by standard statistics techniques. Berndt and Christensen (1973b) test the symmetry restrictions in a translog input function and their data provide support for the existence of symmetry. In our paper, we simply impose symmetry restrictions.

$$
\begin{aligned}
s_L &= \beta_L + \gamma_{LL} \ln \frac{L}{K} + \gamma_{LS} \ln \frac{S}{K} + \gamma_{LT} \ln \frac{T}{K}, \\
s_S &= \beta_S + \gamma_{LS} \ln \frac{L}{K} + \gamma_{SS} \ln \frac{S}{K} + \gamma_{ST} \ln \frac{T}{K}, \\
s_T &= \beta_T + \gamma_{LT} \ln \frac{L}{K} + \gamma_{ST} \ln \frac{S}{K} + \gamma_{TT} \ln \frac{T}{K}.
\end{aligned} \tag{9}
$$

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 equation (9).

We define

$$y_i^{'} = \left[\begin{array}{ccc} s_L & s_S & s_T \end{array} \right],$$

$$\beta^{'} = \left[\begin{array}{ccccccccc} \beta_L & \gamma_{LL} & \gamma_{LS} & \gamma_{LT} & \beta_S & \gamma_{SS} & \gamma_{ST} & \beta_T & \gamma_{TT} \end{array} \right],$$

and

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

As stated by Berndt and Christensen (1974), there might be a problem of simultaneous-equation bias when estimating $\hat{\beta}$ by ordinary least-squares (OLS). Therefore, we estimate $\hat{\beta}$ by feasible generalized least-squares (FGLS) as

$$\hat{\beta} = [X^{'}(\hat{\Omega} \otimes I_N)^{-1} X]^{-1} X^{'}(\hat{\Omega} \otimes I)^{-1} y, \tag{10}$$

with Ω as the variance–covariance matrix and I as an identity matrix.

To estimate $\hat{\beta}$, we first perform OLS estimation of equation (9) to obtain each s_i^{OLS} and their respective residuals. We then construct the variance–covariance matrix $\hat{\Omega}$ of the residuals and take the Kronecker product of $\hat{\Omega}$ and an identity matrix. After that, we compute $\hat{\beta}$, determined by equation (10).

As discussed in Section II, we use the translog function to compute the elasticity of complementarity between the four inputs considered in our specifications. We use $\hat{\beta}$ to estimate $\hat{s}_i$ and construct the estimated elasticities of complementarity $\hat{c}_{ij}$. We compute 95 percent confidence intervals for $\hat{c}_{ij}$ using the bootstrap method.[20] Finally, we use the estimated elasticities of complementarity, $\hat{c}_{ij}$, to quantify the effect of capital composition changes on the skill wage premium, as discussed in Section II.

Note that the values of the elasticities of complementarity vary with the level of input usage when estimated using a flexible functional form. Hence, we present point estimates of the elasticities evaluated at the sample means. However, as argued by Frondel and Schmidt (2006), it might be the case that elasticities tend to expose the particular economic circumstances in effect when cost shares are estimated. Therefore, following Frondel and Schmidt (2006), we analyze the effect of changes in capital composition on the skill wage premium considering both factual and counterfactual elasticities of complementarity.[21]

Moreover, another problem is that technological shocks might affect the production function and thus our results. Using year effects would allow us to control for technological shocks, which might affect the whole Chilean manufacturing sector. However, there would also be technological shocks that might affect particular industries within the Chilean manufacturing sector. Therefore, we construct an additional variable that is the interaction between year and industry effects.[22] We then follow two procedures to estimate $\hat{\beta}$: the first without including the interaction between year and industry effects (the pooled FGLS approach), and the second including the interaction between year and industry effects (the interaction FGLS approach).

Berndt and Christensen (1974) suggest performing three-stage least-squares (3SLS) estimation to control a problem of simultaneous-equation bias when performing OLS. Therefore, as a check of robustness to our pooled and interaction FGLS approaches, following Zellner and Theil (1962), we perform 3SLS estimation. We use export income as a percentage of total income, percentage of foreign investment, communications expenditure, Internet Protocol telephony, and Internet connection as instruments. To test the instruments' relevance, we use the Staiger and Stock (1997) condition of relevance. We also test the instruments' exogeneity using the J-statistic of the Hansen test.

Finally, we must discuss the regularity conditions for the translog function. A test on the translog specification requires one to assess the monotonicity and strict convexity of the isoquants of the translog function. In general, the translog function does not satisfy these restrictions globally. This follows from the quadratic nature of the translog function. However,

[20] We perform the non-parametric bootstrap method (resampling with replacement) with 1,000 replications.
[21] See also Frondel and Schmidt (2002, 2003) for discussions on related issues.
[22] For the industry effects, we consider ISIC at the two-digit level.

as discussed by Berndt and Christensen (1973b), there are regions in the input space where these conditions can be satisfied. These well-behaved regions might be large enough that the translog function can provide a good representation of the relevant production possibilities.

Monotonicity requires that $F_i > 0$. An equivalent condition is that $s_i > 0$. Therefore, monotonicity can be evaluated at each data point by checking that the predicted cost shares are positive. The isoquants of the translog function F are strictly convex if the corresponding bordered Hessian matrix of the first and second partial derivatives is negative definite. This can also be evaluated at each data point for the estimated translog function. We perform this analysis in Section V.

V. Empirical Results

We first test capital–skill complementarity considering the aggregate level of capital; that is, without distinguishing between technological and non-technological capital. Defining $Z = T + K$ as the aggregate stock of capital, Table 1 presents the results regarding the elasticities of complementarity.[23] We observe in Table 1 that the elasticity of complementarity between aggregate capital and skilled labor ($\hat{c}_{ZS}$) is larger than the elasticity of complementarity between aggregate capital and unskilled labor ($\hat{c}_{ZL}$). Therefore, our results empirically support the existence of capital–skill complementarity. As discussed in Section I, this result might be an interesting candidate to explain why most developing countries have experienced a rise in the skill premium in recent decades.

Next, we assess how the technological content of the capital stock affects the size of capital–skill complementarity. To do so, we compare the aggregate and disaggregate elasticities of complementarity, using the two specifications described in Section III. Table 2 shows the elasticities of complementarity.[24] We can see that there are both technological and non-technological capital–skill complementarity for all specifications,

[23]Table A1 in Appendix A shows the coefficients of equation (9) for this aggregate specification. We can also see in Table A1 the F-statistics of the first stage of the 3SLS regressions to evaluate the Staiger and Stock (1997) condition of the instruments' relevance, and the J-statistics, with their corresponding p-values, of the Hansen test of the instruments' exogeneity. We observe that the F-statistic is larger than 10 in every case, satisfying the Staiger and Stock (1997) condition of relevance. Moreover, as we can observe from the p-value of every J-statistic, we fail to reject the null hypothesis of the Hansen test, that the instruments are exogenous, at any conventional level of significance. Therefore, our instruments satisfy both the relevance and exogeneity conditions.
[24]Table A2 of Appendix A shows the pooled and interaction FGLS estimations, and the 3SLS estimations of equation (9) coefficients for the disaggregate specifications. Table A2 also exhibits the F-statistics of the first stage of the 3SLS regressions to evaluate the instruments' relevance,

Table 1. *Elasticities of complementarity for the aggregate specification*

Elasticity	Pooled FGLS	Interaction FGLS	3SLS
$\hat{c}_{ZS}$	0.7618	0.7771	0.2675
	[0.7545, 0.7690]	[0.7694, 0.7848]	[0.2353, 0.3027]
$\hat{c}_{ZL}$	0.7346	0.7299	0.2120
	[0.7269, 0.7416]	[0.7222, 0.7369]	[0.2036, 0.2197]
$\hat{c}_{LS}$	0.7515	0.7537	1.1015
	[0.7489, 0.7540]	[0.7511, 0.7562]	[1.0927, 1.1112]
$\hat{c}_{ZZ}$	−3.0650	−3.0747	−0.9541
	[−3.1192, −3.0091]	[−3.1291, −3.0178]	[−0.9835, −0.9271]
$\hat{c}_{LL}$	−0.6982	−0.6877	−0.6837
	[−0.7007, −0.6763]	[−0.7001, −0.6757]	[−0.6859, −0.6817]
$\hat{c}_{SS}$	−1.8928	−1.9074	−2.1923
	[−1.9264, −1.8578]	[−1.9416, −1.8725]	[−2.2342, −2.1545]
$\hat{c}_{ZS} - \hat{c}_{ZL}$	0.0272	0.0472	0.0555

Notes: 95 percent bootstrap confidence intervals are shown in square brackets.

regardless of the estimation method used. Moreover, we observe that under all specifications, $\hat{c}_{TS} - \hat{c}_{TL} > \hat{c}_{KS} - \hat{c}_{KL}$ and, therefore, the capital–skill complementarity grows larger as the technological content of capital increases. We also find that when we use the most high-tech definition of technological capital (software), technological capital–skill complementarity ($\hat{c}_{TL} - \hat{c}_{TS}$) increases more than non-technological capital–skill complementarity ($\hat{c}_{KL} - \hat{c}_{KS}$). Therefore, capital composition matters: capital–skill complementarity grows as the technological content of capital rises.[25]

We also discuss the order of the elasticity of complementarity between non-technological capital and skilled labor (c_{KS}) and the elasticity of complementarity between technological capital and unskilled labor (c_{TL}). Whenever $c_{KS} > c_{TL}$, we can conclude that non-technological capital is more complementary to skilled workers than technological capital is to unskilled workers. We observe from Table 2 that $\hat{c}_{KS} > \hat{c}_{TL}$ holds in all specifications. However, we can also see from this table that this effect

and the J-statistics, with their corresponding p-values, to evaluate the instruments' exogeneity. As the F-statistic is larger than 10 in every case, satisfying the Staiger and Stock (1997) condition of relevance, we conclude that our instruments are relevant. Considering the p-values of the J-statistics, which fail to reject the null hypothesis of the instruments' exogeneity at any conventional level of significance, we also conclude that our instruments are exogenous.

[25]Appendix B shows the relationship between the partial elasticities of complementarity and the partial elasticities of substitution. Table B1 in Appendix B presents the estimates of the implied partial elasticities of substitution.

Table 2. *Elasticities of complementarity for the disaggregate specifications*

	Pooled FGLS		Interaction FGLS		3SLS	
Elasticity	Specification 1	Specification 2	Specification 1	Specification 2	Specification 1	Specification 2
$\hat{c}_{KS}$	0.7350	0.7608	0.7570	0.7794	1.1488	0.8778
	[0.7191, 0.7509]	[0.7395, 0.7816]	[0.7416, 0.7731]	[0.7573, 0.8006]	[1.0617, 1.2720]	[0.7997, 0.9338]
$\hat{c}_{KL}$	0.6866	0.7510	0.6837	0.7377	0.2033	0.6088
	[0.6692, 0.7016]	[0.7346, 0.7659]	[0.6667, 0.6983]	[0.7214, 0.7527]	[0.1666, 0.2321]	[0.4310, 0.7370]
$\hat{c}_{TS}$	0.3043	0.7753	0.3201	0.7998	4.1712	0.7892
	[0.1877, 0.4166]	[0.7573, 0.7929]	[0.2113, 0.4229]	[0.7829, 0.8175]	[3.7358, 4.6040]	[0.7283, 0.8381]
$\hat{c}_{TL}$	0.0839	0.7205	0.1099	0.7231	−2.5869	0.3119
	[0.0014, 0.1641]	[0.7072, 0.7331]	[0.0239, 0.1891]	[0.7096, 0.7353]	[−2.6994, −2.4765]	[0.2272, 0.3895]
$\hat{c}_{KT}$	−0.5531	0.7123	−0.5979	0.7597	1.2225	2.0479
	[−0.7982, −0.3031]	[0.6367, 0.7856]	[−0.8300, −0.3569]	[0.6810, 0.8332]	[1.0015, 1.4647]	[1.6939, 2.4477]
$\hat{c}_{LS}$	0.7586	0.7477	0.7601	0.7494	1.6388	0.7870
	[0.7535, 0.7638]	[0.7430, 0.7524]	[0.7550, 0.7653]	[0.7450, 0.7541]	[1.6106, 1.6738]	[0.7736, 0.8034]
$\hat{c}_{KK}$	−2.7179	−8.9939	−2.7363	−9.0272	−1.9465	−13.1956
	[−2.8075, −2.6264]	[−9.2961, −8.6769]	[−2.8243, −2.6471]	[−9.3307, −8.7062]	[−2.0084, −1.8845]	[−14.0238, −12.0913]
$\hat{c}_{TT}$	−9.7801	−5.7133	−22.0583	−5.8114	−95.6004	−4.2947
	[−69.2850, 57.0935]	[−5.9123, −5.5308]	[−82.3024, 49.2921]	[−6.0105, −5.6331]	[−98.5870, −92.6139]	[−4.6897, −3.8255]
$\hat{c}_{LL}$	−0.5922	−0.5808	−0.5918	−0.5802	−0.7996	−0.5741
	[−0.6089, −0.5753]	[−0.5969, −0.5654]	[−0.6087, −0.5747]	[−0.5966, −0.5647]	[−0.8129, −0.7892]	[−0.5959, −0.5502]
$\hat{c}_{SS}$	−2.3285	−2.2785	−2.3504	−2.2993	−4.6502	−1.9593
	[−2.3995, −2.2579]	[−2.3483, −2.2086]	[−2.4193, −2.2785]	[−2.3678, −2.2294]	[−4.8280, −4.5202]	[−2.0013, −1.9151]
$\hat{c}_{KS} - \hat{c}_{KL}$	0.0484	0.0098	0.0733	0.0417	0.9385	0.2690
$\hat{c}_{TS} - \hat{c}_{TL}$	0.2204	0.0548	0.2102	0.0767	6.7581	0.4773
$\hat{c}_{KS} - \hat{c}_{TL}$	0.6511	0.0403	0.6471	0.0563	3.7287	0.5659
$\hat{c}_{KL} - \hat{c}_{TS}$	0.3823	−0.0243	0.3636	−0.0621	−3.9679	−0.1804

Notes: 95 percent bootstrap confidence intervals are shown in square brackets.

is weaker when we consider less high-tech definitions of technological capital.

What is the impact of our results on the skill wage premium? Table 3 shows the result of equation (7) for different changes in capital composition using the elasticities of complementarity estimated by the pooled FGLS approach for specification 1. Following Frondel and Schmidt (2006), we consider in the analysis both factual and counterfactual elasticities. We first analyze the relative input growth in our database to construct counterfactual elasticities. We observe in the data that the relative growth of skilled labor tends to increase in 2011. Therefore, we split the database into two subsamples, one covering the years 2008 to 2010 (subsample 0) and the other covering 2011 (subsample 1). Column two of Table 3 shows the SPE using elasticities of complementarity estimated from the whole sample, $\hat{c}_{ij}(\beta^*, i^*)$. The third and fourth columns show the SPE using factual elasticities from subsample 0, $\hat{c}_{ij}(\beta^0, i^0)$, and subsample 1, $\hat{c}_{ij}(\beta^1, i^1)$, respectively. The fifth column shows the SPE using counterfactual elasticities constructed with estimated parameters from subsample 0 and input shares from subsample 1, $\hat{c}_{ij}(\beta^0, i^1)$. Column six shows the SPE using counterfactual elasticities constructed with estimated parameters from subsample 1 and input shares from subsample 0, $\hat{c}_{ij}(\beta^1, i^0)$. Column seven displays the SPE using counterfactual elasticities considering estimated parameters from subsample 0 and input shares from the whole sample, $\hat{c}_{ij}(\beta^0, i^*)$. Finally, the eighth column displays the SPE using counterfactual elasticities built with estimated parameters from subsample 1 and input shares from the whole sample, $\hat{c}_{ij}(\beta^1, i^*)$.

Table 3. *SPE of capital composition change for the pooled FGLS approach for specification 1*

$\widetilde{s}_T$	$\hat{c}_{ij}(\beta^*, i^*)$	$\hat{c}_{ij}(\beta^0, i^0)$	$\hat{c}_{ij}(\beta^1, i^1)$	$\hat{c}_{ij}(\beta^0, i^1)$	$\hat{c}_{ij}(\beta^1, i^0)$	$\hat{c}_{ij}(\beta^0, i^*)$	$\hat{c}_{ij}(\beta^1, i^*)$
0.05	0.0086	0.0099	0.0056	0.0045	0.0109	0.0081	0.0092
0.10	0.0172	0.0199	0.0112	0.0089	0.0217	0.0162	0.0184
0.15	0.0258	0.0298	0.0168	0.0134	0.0326	0.0243	0.0275
0.20	0.0344	0.0398	0.0224	0.0179	0.0434	0.0324	0.0367
0.25	0.0430	0.0497	0.0280	0.0223	0.0543	0.0405	0.0459
0.30	0.0516	0.0596	0.0336	0.0268	0.0651	0.0486	0.0551
0.35	0.0602	0.0696	0.0392	0.0313	0.0760	0.0567	0.0643
0.40	0.0688	0.0795	0.0449	0.0357	0.0868	0.0649	0.0735
0.45	0.0774	0.0894	0.0505	0.0402	0.0977	0.0730	0.0826
0.50	0.0860	0.0994	0.0561	0.0446	0.1086	0.0811	0.0918

Notes: The SPE effect measures how changes in capital composition affect the skill wage premium, given the partial elasticities of complementarity.

We note from the second column of Table 3 that an economy with an increase in the contribution of technological capital to output ($\widetilde{s}_T$) equal to 5 percent experiences an increase of 0.9 percent in the skill wage premium, whereas an economy that has an $\widetilde{s}_T$ equal to 50 percent after replacing non-technological capital with technological capital will experience a rise in the skill wage premium of 8.6 percent. Regarding the rest of the columns of Table 3, it can be seen that although the SPE might vary in magnitude according different factual and counterfactual elasticities of complementarity, the qualitative result is the same. Indeed, when there is an increase in the contribution of technological capital to output of 50 percent, the SPE ranges from 4.5 percent to 10.9 percent.

Finally, we have to check whether regularity conditions for the translog function hold for our estimations. We find that the fitted cost shares from FGLS and 3SLS estimations are positive for about 95 percent of observations. Moreover, we find that the bordered Hessian is negative definite at roughly 90 percent of data points under the FGLS and 3SLS estimations. Therefore, the estimated translog function is monotonic and has strictly convex isoquants in most of the neighborhood covered by our dataset.

VI. Conclusion

Using data from Chilean manufacturing plants, we find that capital is less substitutable for skilled labor than for unskilled labor, supporting the Griliches (1969) capital–skill complementarity hypothesis in the case of a developing country.

Moreover, we find that technological capital–skill complementarity is significantly larger than 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 the complementarity between capital and skilled labor. We show that when technological capital–skill complementarity is larger than non-technological capital–skill complementarity, a change in the composition of the stock of capital toward more technological capital pushes the skill wage premium up.

Traditional capital–skill complementarity models predict that the skill wage premium increases as the stock of capital increases. However, our framework shows that the skill wage premium can increase even when the stock of capital remains roughly constant, as long as non-technological capital is replaced with technological capital. Indeed, we show that an economy that experiences a rise in the contribution of technological capital to output of 50 percent, with a fall in the contribution of non-technological capital of the same magnitude, might face an increase in the skill wage premium of up to 9 percent.

Overall, our results highlight the fact that not only the accumulation of aggregate capital but also changes in capital composition matter for understanding changes in the skill wage premium.

Appendix A: Additional Tables

Table A1. *Coefficients of equation* (9) *for the aggregate specification*

	Pooled FGLS		Interaction FGLS		3SLS	
	s_L	s_S	s_L	s_S	s_L	s_S
$\ln(L/Z)$	0.0638***	−0.0368***	0.0639***	−0.0365***	0.0650***	0.0150
	(0.000320)	(0.000215)	(0.000319)	(0.000214)	(0.009836)	(0.019790)
$\ln(S/Z)$	−0.0368***	0.0501***	−0.0365***	0.0489***	0.0150	0.0258
	(0.000215)	(0.000246)	(0.000214)	(0.000244)	(0.019790)	(0.043839)
β	0.4670***	0.4160***	-6.91×10^{-11}	8.22×10^{-10}	0.6452***	0.3890***
	(0.00130)	(0.00131)	(0.00110)	(0.00104)	(0.064397)	(0.142182)
Observations	33,003	33,003	33,003	33,003	33,003	33,003
F-statistic	–	–	–	–	30.1993	22.6315
J-statistic	–	–	–	–	5.0932	1.6084
					[0.1651]	[0.6575]

Notes: Standard errors are shown in parentheses. ***, **, and * denote significance at the 1, 5, and 10 percent levels, respectively. The p-values are given in square brackets.

Appendix B: Relationship of the Partial Elasticities of Complementarity and Substitution

The partial elasticity of complementarity, denoted by c_{ij}, computes the effect on the price of factor i of a change in the quantity of factor j, holding the marginal cost and quantities of other factors constant. The Allen partial elasticity of substitution, which we hereafter denote by σ_{ij}, registers the effect on the quantity demanded of factor i of a change in the price of factor j, holding output and other factor prices constant. In this Appendix, we derive a formal mathematical relationship between c_{ij} and σ_{ij}.

Let the four-factor production function be $Y = F(L, S, T, K)$. Allen originally defined the partial elasticity of substitution in terms of the properties of the production function as

$$\sigma_{ij} = \frac{F}{i \times j}\frac{H_{ij}^F}{H^F},$$

Table A2. *Coefficients of equation* (9) *for the disaggregate specifications*

	Pooled FGLS			Interaction FGLS			3SLS		
	s_L	s_S	s_T	s_L	s_S	s_T	s_L	s_S	s_T
Specification 1									
$\ln(L/K)$	0.0681***	−0.0324***	−0.000368***	0.0682***	−0.0322***	−0.000357***	0.0039	0.0864	−0.0012***
	(0.000582)	(0.000380)	(1.62×10^{-5})	(0.000578)	(0.000379)	(1.62×10^{-5})	(0.039348)	(0.053739)	(0.000400)
$\ln(S/K)$	−0.0324***	0.0458***	−0.000124***	−0.0322***	0.0445***	−0.000121***	0.0864	−0.0942	0.0005
	(0.000380)	(0.000435)	(1.10×10^{-5})	(0.000379)	(0.000431)	(1.11×10^{-5})	(0.053739)	(0.074597)	(0.000776)
$\ln(T/K)$	−0.000368***	−0.000124***	0.000724***	−0.000357***	−0.000121***	0.000717***	−0.0012***	0.0005	0.0007***
	(1.62×10^{-5})	(1.10×10^{-5})	$(1.47\times{}^{1}0{-}5)$	$(1.62\times10^{-5}$	$(1.11\times{}^{1}0{-}5)$	$(1.48\times{}^{1}0{-}5)$	(0.000399)	(0.000776)	(0.000222)
β	0.5170***	0.3780***	0.0074***	2.51×10^{-9}	8.86×10^{-10}	0.0000	0.8785***	0.0164	0.0083***
	(0.00231)	(0.00236)	(0.000153)	(0.00181)	(0.00176)	(4.22×10^{-5})	(0.1273)	(0.177570)	(0.001475)
Observations	6,293	6,293	6,293	6,293	6,293	6,293	6,293	6,293	6,293
F-statistic	–	–	–	–	–	–	170.4800	36.4984	635.6559
J-statistic	–	–	–	–	–	–	9.3448	4.5806	6.6214
	–	–	–	–	–	–	[0.3141]	[0.8013]	[0.5780]
Specification 2									
$\ln(L/K)$	0.0637***	−0.0351***	−0.0179***	0.0639***	−0.0349***	−0.0177***	0.0893***	−0.0325***	−0.0440***
	(0.000558)	(0.000376)	(0.000370)	(0.000555)	(0.000376)	(0.000363)	(0.002864)	(0.000964)	(0.002109)
$\ln(S/K)$	−0.0351***	0.0461***	−0.00636***	−0.0349***	0.0448***	−0.00567***	−0.0325***	0.0420***	−0.0074***
	(0.000376)	(0.000429)	(0.000289)	(0.000376)	(0.000424)	(0.000283)	(0.000964)	(0.000862)	(0.000750)
$\ln(T/K)$	−0.0179***	−0.00636***	0.0268***	−0.0177***	−0.00567***	0.0255***	−0.0440***	−0.0074***	0.0434***
	(0.000370)	(0.000289)	(0.000435)	(0.000363)	(0.000283)	(0.000428)	(0.002109)	(0.000750)	(0.001957)
β	0.476***	0.367***	0.0928***	-5.78×10^{-10}	1.79×10^{-9}	-1.02×10^{-9}	0.4150	0.4020	0.1234
	(0.00210)	(0.00212)	(0.00147)	(0.00183)	(0.00176)	(0.00120)	(0.006719)	(0.005593)	(0.005061)
Observations	31,996	31,996	31,996	31,996	31,996	31,996	31,996	31,996	31,996
F-statistic	–	–	–	–	–	–	26.4853	120.9193	54.6901
J-statistic	–	–	–	–	–	–	6.1796	14.5565	11.8268
							[0.8000]	[0.1491]	[0.2968]

Notes: Standard errors are shown in parentheses. ***, **, and * denote significance at the 1, 5, and 10 percent levels, respectively. The p-values are given in square brackets.

where H^F is the bordered Hessian determinant of the production function F and H_{ij}^F is the cofactor of F_{ij} in H_{ij}^F. Alternatively, H_{ij}^F/H^F is the element in the $i+1$th row and $j+1$th column of the inverse matrix of the bordered Hessian of F, which we denote hereafter by $\overline{F}$. In turn, the bordered Hessian of F is associated with the comparative statistics of the equilibrium system derived from the cost minimization problem. $\overline{F}$ takes the following form:

$$\overline{F} = \begin{bmatrix} 0 & F_L & F_S & F_K & F_T \\ F_L & F_{LL} & F_{LS} & F_{LK} & F_{LT} \\ F_S & F_{SL} & F_{SS} & F_{SK} & F_{ST} \\ F_K & F_{KL} & F_{KS} & F_{KK} & F_{KT} \\ F_T & F_{TL} & F_{TS} & F_{TK} & F_{TT} \end{bmatrix}.$$

Each element of the matrix $\overline{F}$ can be directly computed by taking the derivative of the production function with respect to the corresponding element:

$$F_i = \frac{\partial \ln F}{\partial \ln \ i} \frac{F}{i}, \tag{B1}$$

$$F_{ii} = \frac{F}{i^2}\left[\frac{\partial(\partial \ln F/\partial \ln \ i)}{\partial \ln \ i} - \frac{\partial \ln F}{\partial \ln i} + \left(\frac{\partial \ln F}{\partial \ln i}\right)^2\right], \tag{B2}$$

$$F_{ij} = \frac{F}{i \times j}\left[\frac{\partial(\partial \ln F/\partial \ln i)}{\partial \ln \ j} + \frac{\partial \ln F}{\partial \ln \ i}\frac{\partial \ln F}{\partial \ln \ j}\right]. \tag{B3}$$

Using the fact that $\partial \ln F/\partial \ln \ i = s_i$ and defining $\gamma_{ii} = \partial(\partial \ln F/\partial \ln \ i)/\partial \ln \ i$ and $\gamma_{ij} = \partial(\partial \ln F/\partial \ln \ i)/\partial \ln \ j$, we can express equations (B1), (B2), and (B3) as

$$F_i = \frac{F}{i} s_i, \tag{B4}$$

$$F_{ii} = \frac{F}{i^2}(\gamma_{ii} - s_i + s_i^2), \tag{B5}$$

$$F_{ij} = \frac{F}{i \times j}(\gamma_{ij} + s_i s_j). \tag{B6}$$

Moreover, we have defined in Section II the partial elasticity of complementarity as $c_{ij} = FF_{ij}/F_iF_j$ (see Sato and Koizumi, 1973). Using (B5), (B6), the definition of γ_{ii} and γ_{ij}, and the fact that $\partial \ln F/\partial \ln \ i = s_i$, we have that

$$c_{ii} = \frac{\gamma_{ii} - s_i + s_i^2}{s_i^2}, \tag{B7}$$

$$c_{ij} = \frac{\gamma_{ij} + s_i s_j}{s_i s_j}. \tag{B8}$$

Replacing equations (B4)–(B8) in the bordered Hessian of the production function, $\overline{F}$, we have that

$$\overline{F} = \begin{bmatrix} 0 & \frac{F}{L}s_L & \frac{F}{S}s_S & \frac{F}{K}s_K & \frac{F}{T}s_T \\ \frac{F}{L}s_L & c_{LL}\frac{s_L^2 F}{L^2} & c_{LS}\frac{s_L s_S F}{L\times S} & c_{LK}\frac{s_L s_K F}{L\times K} & c_{LT}\frac{s_L s_T F}{L\times T} \\ \frac{F}{S}s_S & c_{SL}\frac{s_S s_L F}{S\times L} & c_{SS}\frac{s_S^2 F}{S^2} & c_{SK}\frac{s_S s_K F}{S\times K} & c_{ST}\frac{s_S s_T F}{S\times T} \\ \frac{F}{K}s_K & c_{KL}\frac{s_K s_L F}{K\times L} & c_{KS}\frac{s_K s_S F}{K\times S} & c_{KK}\frac{s_K^2 F}{K^2} & c_{KT}\frac{s_K s_T F}{K\times T} \\ \frac{F}{T}s_T & c_{TL}\frac{s_T s_L F}{T\times L} & c_{TS}\frac{s_T s_S F}{T\times S} & c_{TK}\frac{s_T s_K F}{T\times K} & c_{TT}\frac{s_T^2 F}{T^2} \end{bmatrix}.$$

Note that we can express the bordered Hessian of the production function $\overline{F}$ as

$$\overline{F} = F \times S \times C \times S,$$

where F is the production function and matrices S and C are, respectively,

$$S = \begin{bmatrix} 1 & 0 & 0 & 0 & 0 \\ 0 & \frac{s_L}{L} & 0 & 0 & 0 \\ 0 & 0 & \frac{s_S}{S} & 0 & 0 \\ 0 & 0 & 0 & \frac{s_K}{K} & 0 \\ 0 & 0 & 0 & 0 & \frac{s_T}{T} \end{bmatrix},$$

$$C = \begin{bmatrix} 0 & 1 & 1 & 1 & 1 \\ 1 & c_{LL} & c_{LS} & c_{LK} & c_{LT} \\ 1 & c_{SL} & c_{SS} & c_{SK} & c_{ST} \\ 1 & c_{KL} & c_{KS} & c_{KK} & c_{KT} \\ 1 & c_{TL} & c_{TS} & c_{TK} & c_{TT} \end{bmatrix}.$$

Denote by $\widetilde{C}_{ij}$ the element in the $i + 1$th column and $j + 1$th row of the inverse matrix of C. Analogously, denote by $\widetilde{\overline{F}}_{ij}$ the element in the $i + 1$th column and $j + 1$th row of the inverse matrix of $\overline{F}$. Then,

$$\widetilde{\overline{F}}_{ij} = \frac{1}{F}\frac{\widetilde{C}_{ij}}{(s_i/i)(s_j/j)}.$$

Table B1. *Allen partial elasticities of substitution for the disaggregate specifications*

Elasticity	Pooled FGLS		Interaction FGLS		3SLS	
	Specif. 1	Specif. 2	Specif. 1	Specif. 2	Specif. 1	Specif. 2
$\hat{\sigma}_{KS}$	1.2560	1.3144	1.2761	1.2830	1.1507	1.1331
$\hat{\sigma}_{KL}$	1.2974	1.3319	1.3935	1.3551	2.6527	1.7654
$\hat{\sigma}_{TS}$	8.5364	1.2887	3.7627	1.2463	–2.5170	1.2409
$\hat{\sigma}_{TL}$	12.5036	1.3877	5.3551	1.3814	5.9340	2.4387
$\hat{\sigma}_{KL} - \hat{\sigma}_{KS}$	0.0414	0.0175	0.1174	0.0721	1.5021	0.6323
$\hat{\sigma}_{TL} - \hat{\sigma}_{TS}$	3.9673	0.0990	1.5924	0.1351	8.4510	1.1977

Therefore, using the definition of the partial elasticity of substitution, we finally obtain the following expression for the partial elasticity of substitution:

$$\sigma_{ij} = \frac{1}{s_i s_j} \frac{H_{ij}^C}{H^C}. \tag{B9}$$

Here, H^C is the bordered Hessian determinant of C and H_{ij}^C is the cofactor of C_{ij} in H^C. In turn, H_{ij}^C / H^C is the element in the $i+1$th row and $j+1$th column of the matrix $[C]^{-1}$. Therefore, the partial elasticity of substitution between inputs i and j corresponds to the "inverse" element of the matrix of partial elasticities of complementarity.

In Table B1, we use equation (B9) to estimate the partial elasticities of substitution derived from the computed partial elasticities of complementarity and predicted input shares.

The analysis on the partial elasticity of substitution relies on the concepts of p-complementarity and p-substitution. If two types of inputs are p-complements, this elasticity is negative. If the inputs are p-substitutes, the elasticity is positive. Moreover, when $\sigma_{TL} > \sigma_{TS}$, $\sigma_{KL} > \sigma_{KS}$, and $\sigma_{TL} - \sigma_{TS} > \sigma_{KL} - \sigma_{KS}$, then relative capital–skill p-complementarity exists, and the magnitude of this complementarity grows larger as the technological content of capital increases.

We observe in Table B1 that there are both technological and non-technological relative capital–skill p-complementarity, because $\hat{\sigma}_{KL} - \hat{\sigma}_{KS} > 0$ and $\hat{\sigma}_{TL} - \hat{\sigma}_{TS} > 0$ for all specifications. We also observe that $\hat{\sigma}_{TL} - \hat{\sigma}_{TS} > \hat{\sigma}_{KL} - \hat{\sigma}_{KS} > 0$ and, thus, this relative capital–skill p-complementarity grows larger as the technological content of capital increases. This latter effect is even more pronounced for the most disaggregated definition of technological capital (specification 1).

References

Acemoglu, D. and Zilibotti, F. (2001), Productivity Differences, *Quarterly Journal of Economics 116*, 563–606.

Akay, G. H. and Yuksel, M. (2009), Capital–Skill Complementarity: Evidence from Manufacturing Industries in Ghana, IZA Discussion Paper No. 4674.

Autor, D., Katz, L. F., and Kearney, M. S. (2006), The Polarization of the U.S. Labor Market, *American Economic Review 96* (2), 189–194.

Balleer, A. and van Rens, T. (2013), Skill-Biased Technological Change and the Business Cycle, *Review of Economics and Statistics 95*, 1222–1237.

Bartel, A., Ichniowski, C., and Shaw, K. (2007), How Does Information Technology Affect Productivity? Plant-Level Comparisons of Product Innovation, Process Improvement, and Worker Skills, *Quarterly Journal of Economics 122*, 1721–1758.

Bergstrom, V. and Panas, E. E. (1992), How Robust is the Capital–Skill Complementarity Hypothesis?, *Review of Economics and Statistics 74*, 540–546.

Berman, E., Bound, J., and Griliches, Z. (1994), Changes in the Demand for Skilled Labor within U.S. Manufacturing: Evidence from the Annual Survey of Manufacturers, *Quarterly Journal of Economics 109*, 367–397.

Berndt, E. R. and Christensen, L. R. (1973a), The Internal Structure of Functional Relationships: Separability, Substitution, and Aggregation, *Review of Economic Studies 40*, 403–410.

Berndt, E. R. and Christensen, L. R. (1973b), The Translog Function and the Substitution of Equipment, Structures, and Labor in U.S. Manufacturing 1929–68, *Journal of Econometrics 1*, 81–113.

Berndt, E. R. and Christensen, L. R. (1974), Testing for the Existence of a Consistent Aggregate Index of Labor Inputs, *American Economic Review 64* (3), 391–404.

Bruno, O., Le Van, C., and Masquin, B. (2009), When does a Developing Country Use New Technologies?, *Economic Theory 40*, 275–300.

Cerda, R. A. and Saravia, D. (2009), Corporate Tax, Firm Destruction and Capital Stock Accumulation: Evidence from Chilean Plants, 1979–2004, Central Bank of Chile Working Paper No. 521.

Duffy, J., Papageorgiou, C., and Perez-Sebastian, F. (2004), Capital–Skill Complementarity? Evidence from a Panel of Countries, *Review of Economics and Statistics 86*, 327–344.

Frondel, M. and Schmidt, C. M. (2002), The Capital–Energy Controversy: An Artifact of Cost Shares?, *Energy Journal 23*, 53–79.

Frondel, M. and Schmidt, C. M. (2003), Rejecting Capital–Skill Complementarity at All Costs, *Economics Letters 80*, 15–21.

Frondel, M. and Schmidt, C. M. (2006), The Empirical Assessment of Technology Differences: Comparing the Comparable, *Review of Economics and Statistics 88*, 186–192.

Gallego, F. (2011), Skill Premium in Chile: Studying Skill Upgrading in the South, *World Development 68*, 29–51.

Goldin, C. and Katz, L. F. (1998), The Origins of Technology–Skill Complementarity, *Quarterly Journal of Economics 113*, 693–732.

Gordon, R. J. (1990), *The Measurement of Durable Goods Prices*, University of Chicago Press, Chicago.

Griliches, Z. (1969), Capital–Skill Complementarity, *Review of Economics and Statistics 51*, 465–468.

Hamermesh, D. S. (1985), Substitution between Different Categories of Labour, Relative Wages and Youth Unemployment, *OECD Journal: Economic Studies 5*, 57–85.

Krueger, A. B. (1993), How Computers Have Changed the Wage Structure: Evidence from Microdata, 1984–1989, *Quarterly Journal of Economics 108*, 33–60.

Krugman, P. (1979), A Model of Innovation, Technology Transfer, and the World Distribution of Income, *Journal of Political Economy 87*, 253–366.

Krusell, P., Ohanian, L. E., Ríos-Rull, J.-V., and Violante, G. L. (2000), Capital–Skill Complementarity and Inequality: A Macroeconomic Analysis, *Econometrica 68*, 1029–1053.

Levinsohn, J. (1999), Employment Responses to International Liberalization in Chile, *Journal of International Economics 47*, 321–344.

Levinsohn, J. and Petrin, A. (2003), Estimating Production Functions Using Inputs to Control for Unobservables, *Review of Economic Studies 70*, 317–341.

Liu, L. (1993), Entry–Exit, Learning, and Productivity Change Evidence from Chile, *Journal of Development Economics 42*, 217–242.

Oulton, N. and Srinivasan, S. (2003), Capital Stocks, Capital Services, and Depreciation: An Integrated Framework, Bank of England Working Paper No. 192.

Papageorgiou, C. and Chmelarova, V. (2005), Nonlinearities in Capital–Skill Complementarity, *Journal of Economic Growth 10*, 59–89.

Parro, F. (2013), Capital–Skill Complementarity and the Skill Premium in a Quantitative Model of Trade, *American Economic Journal: Macroeconomics 5*, 72–117.

Pavcnik, N. (2002), Trade Liberalization, Exit, and Productivity Improvement: Evidence from Chilean Plants, *Review of Economic Studies 69*, 245–276.

Polgreen, L. A. and Silos, P. (2008), Capital–Skill Complementarity and Inequality: A Sensitivity Analysis, *Review of Economic Dynamics 11*, 302–313.

Ruiz-Arranz, M. (2003), Wage Inequality in the U.S.: Capital–Skill Complementarity vs. Skill-Biased Technological Change, mimeo.

Sato, R. and Koizumi, T. (1973), On the Elasticities of Substitution and Complementarity, *Oxford Economic Papers 25*, 44–56.

Staiger, D. and Stock, J. H. (1997), Instrumental Variables Regression with Weak Instruments, *Econometrica 65*, 557–586.

Stern, D. I. (2011), Elasticities of Substitution and Complementarity, *Journal of Productivity Analysis 36*, 79–89.

Tanaka, H. (2006), Dynamic Analysis of Imitation and Technology Gap, *Journal of Economics 87*, 209–240.

Tybout, J., de Melo, J., and Corbo, V. (1991), The Effects of Trade Reforms on Scale and Technical Efficiency: New Evidence from Chile, *Journal of International Economics 31*, 231–250.

Yasar, M. and Paul, C. J. M. (2008), Capital–Skill Complementarity, Productivity and Wages: Evidence from Plant-Level Data for a Developing Country, *Labour Economics 15*, 1–17.

Zellner, A. and Theil, H. (1962), Three-Stage Least Squares: Simultaneous Estimation of Simultaneous Equations, *Econometrica 30*, 54–78.

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