Capital-Skill Complementarity: Does capital disaggregation matter?

Juan A. Correa* Miguel Lorca† Francisco Parro‡

Abstract

Using Chilean manufacturing plants data, we find: (1) the elasticity of substitution between capital and skilled labor is lower than the elasticity of substitution between capital and unskilled labor, (2) the higher the technological component of the capital stock the larger the size of complementarity between capital and skilled labor, and (3) significant heterogeneity across group of industries. Our findings allow reconciling the observed rise in the skill premium with trade liberalization in developing countries. Additionally, they 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
JEL Classification: D24, J24, L60

I. Introduction

Since Griliches (1969) first stated that capital is less substitutable for skilled labor than for unskilled labor, several studies have attempted to test this hypothesis. Although some of the literature on this topic supports the Griliches (1969) hypothesis, the evidence has been almost exclusively concentrated in developed countries. Additionally, since most of the

*Department of Economics, Pontificia Universidad Católica, Santiago, Chile; and Research Department, Ministry of Finance, Santiago Chile, postal code: 8340487, phone: 56-2-8282017, e-mail address: jlcorrea@hacienda.gov.cl.

†Department of Economics, Universidad de Chile, Santiago, Chile; and Research Department, Ministry of Finance, Santiago Chile, postal code: 8340487, phone: 56-2-8282017, e-mail address: mlorca@hacienda.gov.cl.

‡Department of Economics, Pontificia Universidad Católica, Santiago, Chile; and Research Department, Ministry of Finance, Santiago Chile, postal code: 8340487, phone: 56-2-8282017, e-mail address: fparro@hacienda.gov.cl.

related articles regard capital as an aggregate input and do not consider that there are also differences in the complexity of capital, they 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 cross-sectional data from 4,500 Chilean manufacturing plants, we disaggregate the stock of capital, defining four 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, suporting the Griliches (1969) hypothesis in a developing country.

The existence of capital-skill complementarity can help us understand growing earnings inequality 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 (forthcoming), 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. Therefore, it is difficult to reconcile the observed rise in the skill premium with the trade liberalization that most developing countries have experienced during recent decades.

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 (forthcoming) 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.

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 imported 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. This result may also be important for understanding not only the evolution of the skill premium in a particular economy but also cross-sectional variations of the skill premium within a group of countries at some moment in time.

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.

Another interesting finding from our results is that there is significant heterogeneity across groups of industries in our data. Although the size of capital-skill complementarity for some groups of industries in our database is similar to that found in developed countries, there are other groups of industries in which capital-skill complementarity is much larger than that reported in the literature.

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.

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

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

and skilled labor. Using a U.S. time series between 1963 and 1992,[2] 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 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."

Using a panel of countries, Duffy, Papageorgiou, and Perez-Sebastian (2004) find weak evidence of capital-skill complementarity. In some of their specifications, they even find the surprising result that the hypothesis of capital-skill complementarity is more sustainable with lower thresholds for the definition of skilled labor.[3]

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.

Bartel, Ichniowski, and Shaw (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, Katz, and Kearney (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. It is interesting to note that they find a large capital-skill complementarity size in industries that manufacture food and beverages, wood, and nonmetallic mineral products. In our results, however, capital-skill complementarity in this group of industries does not even hold in some specifications.

Data sets from undeveloped 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

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

[3]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."

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

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 the idea that the composition of capital matters. We find that for the specification with the strictest definition of technological capital, the elasticity of substitution between non-technological capital and skilled labor is 0.68, while the elasticity of substitution between technological capital and skilled labor is -0.08; therefore, technological capital and skilled labor seem to be complements in our data.

The rest of the paper is organized as follows. Section II. presents the econometric model and the construction of the elasticities of substitution. Section III. describes the data that we are working with. Section IV. shows our results and a check of robustness supporting the evidence of capital-skill complementarity and the compensation effect in most of our specifications. Section V. concludes.

II. Econometric Model

A. Translog input function

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

We first define a constant returns to scale and Hicks-neutral 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 function in a translog form as

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

We also assume that markets are competitive; thus, $\frac{\partial F}{\partial L} = P_L$, $\frac{\partial F}{\partial S} = P_S$, $\frac{\partial F}{\partial T} = P_T$, 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

[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 1.2.

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

$$s_L = \beta_L + \gamma_{LL} \ln L + \gamma_{LS} \ln S + \gamma_{LT} \ln T + \gamma_{LK} \ln K,$$

$$s_S = \beta_S + \gamma_{LS} \ln L + \gamma_{SS} \ln S + \gamma_{ST} \ln T + \gamma_{SK} \ln K,$$

$$s_T = \beta_T + \gamma_{LT} \ln L + \gamma_{ST} \ln S + \gamma_{TT} \ln T + \gamma_{TK} \ln K,$$

$$s_K = \beta_K + \gamma_{LK} \ln L + \gamma_{SK} \ln S + \gamma_{TK} \ln T + \gamma_{KK} \ln K.$$

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 the system, we have the factor shares used in the estimation given by

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

We can now solve this system using seemingly unrelated regressions (SUR),[6] defining

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

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

and

$$X_i = \left[\begin{array}{ccccccccc} 1 & \ln \frac{L}{K} & \ln \frac{S}{K} & \ln \frac{T}{K} & 0 & 0 & 0 & 0 & 0 \\ 0 & 0 & \ln \frac{L}{K} & 0 & 1 & \ln \frac{S}{K} & \ln \frac{T}{K} & 0 & 0 \\ 0 & 0 & 0 & \ln \frac{L}{K} & 0 & 0 & \ln \frac{S}{K} & 1 & \ln \frac{T}{K} \end{array} \right].$$

We can estimate $\hat{\beta}$ as

$$\hat{\beta} = (X^{'}(\Omega \otimes I_N)^{-1} X)^{-1} X^{'} (\Omega \otimes I_N)^{-1} y, \tag{2}$$

with Ω as the variance-covariance matrix and I_N an identity matrix of size N.

[6] Any deviation of the cost shares from the logarithmic marginal products is assumed to be the result of errors in optimizing behavior. Therefore, we specify a classical additive disturbance for each of the equations in (1).

B. Elasticities of substitution

Once we have $\hat{\beta}$, we can estimate input shares $\hat{s}_i$ and compute elasticities of substitution using Allen-Uzawa elasticities defined as

$$\hat{\sigma}_{ij} = \frac{\hat{\gamma_{ij}} + \hat{s}_i \hat{s}_j}{\hat{s}_i \hat{s}_j}, \tag{3}$$

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

We then use $\hat{\sigma}_{ij}$ to test whether capital-skill complementarity holds. We define relative capital-skill complementarity as $\hat{\sigma}_{zL} > \hat{\sigma}_{zS}$ and absolute capital-skill complementarity as $\hat{\sigma}_{zL} > 0 > \hat{\sigma}_{zS}$, $\forall z \in \{T, K\}$.

When disaggregating capital, we can also check the order of the elasticity of substitution between non-technological capital and skilled labor ($\hat{\sigma}_{KS}$), and the elasticity of substitution between technological capital and unskilled labor ($\hat{\sigma}_{TL}$). If $\hat{\sigma}_{KS} > \hat{\sigma}_{TL}$ ($\hat{\sigma}_{KS} < \hat{\sigma}_{TL}$), we can argue that a machine is more (or less) substitutable for skilled workers than software is for unskilled workers. We denote this as the compensation (or augmenting) effect.

Whenever capital-skill complementarity holds, there are two cases of analysis to check whether we have the compensation effect ($\hat{\sigma}_{KS} > \hat{\sigma}_{TL}$) or the augmenting effect ($\hat{\sigma}_{KS} < \hat{\sigma}_{TL}$). The first case assumes that $\hat{\sigma}_{TS} > \hat{\sigma}_{KL}$; i.e., the elasticity of substitution between technological capital and skilled labor is larger than the elasticity of substitution between non-technological capital and unskilled labor. Figure 1 shows the relative order of the elasticities of substitution, where the value increases toward the right-hand side. Although we cannot compare $\hat{\sigma}_{KS}$ with $\hat{\sigma}_{TL}$ directly, capital-skill complementarity implies that $\hat{\sigma}_{TL} > \hat{\sigma}_{TS}$ and $\hat{\sigma}_{KL} > \hat{\sigma}_{KS}$. Therefore, $\hat{\sigma}_{TL}$ is unambiguously larger than $\hat{\sigma}_{KS}$ (augmenting effect).

However, if we assume the second case, that $\hat{\sigma}_{TS} < \hat{\sigma}_{KL}$, both effects are possible, as we can see in figure 2. By capital-skill complementarity, we know that $\hat{\sigma}_{KL} > \hat{\sigma}_{KS}$ and $\hat{\sigma}_{TL} > \hat{\sigma}_{TS}$; thus, the order between $\hat{\sigma}_{TL}$ and $\hat{\sigma}_{KS}$ is ambiguous. In this case, whether we have the compensation effect or the augmenting effect depends on the distance of $\hat{\sigma}_{KL}$ to $\hat{\sigma}_{KS}$ and to $\hat{\sigma}_{TL}$.

Since $\hat{\sigma}_{TS} > \hat{\sigma}_{KL}$ means that 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 $\hat{\sigma}_{TS} < \hat{\sigma}_{KL}$. Figure 3 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 $\hat{\sigma}_{KL} > \hat{\sigma}_{KS}$ and $\hat{\sigma}_{TL} > \hat{\sigma}_{TS}$. The latter is the reason why the isoquant in subfigure 3b (subfigure 3d) is more L-shaped than the isoquant in subfigure 3a (subfigure 3c). From $\hat{\sigma}_{TS} < \hat{\sigma}_{KL}$, we also know that the isoquant in subfigure 3d is more

L-shaped than the isoquant in subfigure 3a. What we do not know is whether the isoquant in subfigure 3b is more or less L-shaped than the isoquant in subfigure 3c.

Whenever the isoquant shape in subfigure 3a is more (less) similar to the isoquant shape in subfigure 3b than to that in subfigure 3c; i.e., $\hat{\sigma}_{KL} > \hat{\sigma}_{KS} > \hat{\sigma}_{TL}$ ($\hat{\sigma}_{KL} > \hat{\sigma}_{TL} > \hat{\sigma}_{KS}$), the compensation effect (augmenting effect) holds. We can carry out the equivalent exercise stating that whenever the isoquant shape in subfigure 3d is more (less) similar to the isoquant shape in subfigure 3c than to that in subfigure 3b; i.e., $\hat{\sigma}_{TS} < \hat{\sigma}_{TL} < \hat{\sigma}_{KS}$ ($\hat{\sigma}_{TS} < \hat{\sigma}_{KS} < \hat{\sigma}_{TL}$), the compensation effect (augmenting effect) holds.

Therefore, figure 3 indicates that the compensation effect (augmenting effect) holds whenever horizontal differences are smaller (larger) than vertical differences. The intuition behind this can be seen as a combination of two factors: the user-friendliness of the type of capital, which determines the level of capital-skill complementarity, and the size of the labor substitution generated by the type of capital.

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. If a process uses user-friendly machines, but these machines can perform tasks that would otherwise be performed by a large number of workers, we expect the compensation effect to hold. On the contrary, if machines are complex to use and do not substitute for too many workers, 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) from 2008. 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, de Melo, and Corbo (1991), Liu (1993), Levinsohn (1999), Pavcnik (2002), and Levinsohn and Petrin (2003), among others.

The ENIA 2008 collected information from 4,675 manufacturing plants, providing us with a representative database of the Chilean manufacturing sector. We focus our analysis on the plants that are linked to a particular industry.[7] Thus, we include 4,500 plants operating in 124 industries identified by the International Standard Industrial Classification (ISIC) at the four-digit level.[8]

The data retrieved from the ENIA 2008 include gross fixed assets, depreciation of gross

[7] 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 (only 20 plants are in this situation).

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

fixed assets, investment in fixed assets, labor hours, number of workers, labor compensation, value added, financial cost, corporate taxes, exports, IT expenditure, intermediate expenditure, ownership, location, and ISIC code.

The ENIA 2008 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.[9] 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 type of fixed asset for plant i at time t, δ_k denotes the depreciation rate of fixed asset k,[10] and I is the investment in fixed asset k.[11]

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.[12]

In order to define both technological capital T and non-technological capital K, we build four different specifications. In Specification 1, we define T as software and K as the rest of fixed assets. Since there are both technological and non-technological assets included in the other intangible assets, machinery and equipment, and other tangible fixed assets categories, we define a weighting parameter built as

$$p_i = \frac{IT_i}{IT_i + NIT_i},$$

where IT_i is the information and technology expenditure of plant i and NIT is the raw material expenditure, plus the energy and water expenditure, plus other intermediate expenditure. In Specification 2, we define T as software plus p_i times other intangible assets. In Specification 3, we define T as software plus p_i times the addition of other intangible assets, machinery and equipment, and other tangible fixed assets. Finally, in

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

[10] 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.

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

[12] 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.

Specification 4, 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 31% 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.

Since many industries in our data contain few plants,[13] we construct three groups of industries to test heterogeneity. Following Hatzichronoglou (1997), we define the group "High" as the group of industries that are high or medium-high R&D intensive, "Medium" as those that are medium-low R&D intensive, and "Low" as those that are low R&D intensive. Table 1 shows the industries, at the ISIC-2 level, considered in each group.

IV. Empirical Results

We now estimate the model developed in section II. Our procedure consists first of an OLS estimation of the system equation (1) to obtain each $\hat{s}_i$ and their respective residuals. We then construct the variance-covariance matrix Ω of the residuals and take the Kronecker product of Ω and an identity matrix. After that, we compute $\hat{\beta}$, determined by equation (2). We then use $\hat{\beta}$ to estimate $\hat{s}_i$ and insert them in equation (3) 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.[14] All outcome tables report the mean of the 95% bootstrap confidence intervals, which are constructed using the 2.5% and 97.5% quantiles from the bootstrap distribution.

We first test capital-skill complementarity considering the aggregate level of capital; i.e., without distinguishing between technological and non-technological capital. Defining $Z = T + K$, 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.[15] This result constitutes novel empirical evidence of capital-skill complementarity for a develping economy. As discussed in section I., this result is important since it allows to reconciliate the observed rise in the skill premium with the trade liberalization that most developing

[13]This problem remains even when we aggregate at the ISIC 2-digit level.

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

[15]Table 2 shows the coefficients of equation (1) for the aggregate specification.

countries have experienced in recent decades.

We now compare the aggregate and disaggregate elasticities of substitution, using the four specifications described in section III.. Table 5 shows the elasticities of substitution for the disaggregate specifications.[16] We can see that there is both technological and non-technological capital-skill complementarity for the four 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, whereas technological and non-technological capital-skill complementarity are very similar in Specification 4.

Another interesting result, which can be analyzed from Table 5, is that the compensation effect holds in three of the four 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. We can even observe that the augmenting effect holds in Specification 4 ($\hat{\sigma}_{KS} < \hat{\sigma}_{TL}$). As both $\hat{\sigma}_{KL}$ and $\hat{\sigma}_{KS}$ remain very similar in the four 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.

To show how heterogeneous the industry groups are, we test capital-skill complementarity considering the Hatzichronoglou (1997) groups defined in the previous section. As shown in Table 6, we find capital-skill complementarity in most of the cases. However, in Specifications 1, 2, and 3, technological capital-skill complementarity does not hold in the Low group of industries.[17] We can also see that, in Specification 4, non-technological capital-skill complementarity does not hold in the High group of industries. An interesting pattern of these results is that while $\hat{\sigma}_{TL}$ is roughly the same across the four specifications in the High group of industries, it increases in both the Medium and Low groups of industries as soon as we use more aggregate definitions of technological capital.

Bergstrom and Panas (1992) show capital-skill complementarity heterogeneity across nine Swedish manufacturing industries. It is interesting to observe that some of their results contrast with ours. They find a large capital-skill complementarity size in some industries, such as "Manufacture of paper and paper products" and "Manufacture of food products and beverages." However, these industries are in the Low group, which shows the smaller size of non-technological capital-skill complementarity and even no technological capital-skill complementarity at all, in most of our specifications.

We check the robustness of our results, including some control variables: plant size,[18]

[16]Table 4 shows the coefficients of equation (1) for the disaggregate specifications.

[17]Although $\hat{\sigma}_{TL} > \hat{\sigma}_{TS}$, the 95% bootstrap confidence intervals overlap.

[18]We control for five different plant sizes: 15 workers or fewer, more than 15 workers and fewer than

region where the plant is located, exports, and percentage of foreign ownership.

As we can see in tables 7, 8, and 9, the results are roughly the same when control variables are included the results are roughly the same for the aggregate and disaggregate specifications and for the groups of industries.

V. 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. This result allows us to understand why the skill premium in some developing countries has increased after the trade liberalization process of the 1980s and 1990s. Capital-skill complementarity counterbalances the negative effect of trade openness on the skill premium that traditional trade theories predict.

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. This finding is important for two reasons. First, it shows that the composition of capital imports matters. As the share of technological capital imports increases, *ceteris paribus*, an increase in capital imports may raise the skill premium to a greater extent. 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. Second, our 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

31 workers, more than 30 workers and fewer than 51 workers, more than 50 workers and fewer than 101 workers, and more than 100 workers.

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.

Finally, we present evidence of significant heterogeneity across group of industries. Although the size of capital-skill complementarity for some groups of industries in our database is similar to that found in developed countries, there are other groups of industries in which capital-skill complementarity is much larger than that reported in the literature. An empirical evaluation of the forces that make larger the capital-skill complementarity in some industries but smaller in others constitutes an interesting avenue for future research.

References

Akay, G. H. and M. Yuksel (2009). Capital-skill complementarity: Evidence from manufacturing industries in Ghana. IZA D.P. No. 4674.

Allen, R. G. D. (1938). *Mathematical Analysis for Economists.* London: Macmillan and Co.

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

Bartel, A., C. Ichniowski, and K. Shaw (2007). How does information technology affect productivity? plant-level comparisons of product innovation, process improvement, and worker skills. *Quarterly Journal of Economics 122*(4), 1721–1758.

Bergstrom, V. and E. E. Panas (1992). How robust is the capital-skill complementarity hypothesis? *Review of Economics and Statistics 74*(3), 540–546.

Berndt, E. R. and L. R. Christensen (1973). The internal structure of functional relationships: Separability, substitution, and aggregation. *Review of Economic Studies 40*(3), 403–410.

Berndt, E. R. and L. R. Christensen (1974). Testing for the existence of a consistent aggregate index of labor inputs. *American Economic Review 64*(3), 391–404.

Cerda, R. A. and D. Saravia (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., C. Papageorgiou, and F. Perez-Sebastian (2004). Capital-skilll complementarity? evidence from a panel of countries. *Review of Economics and Statistics 86*(1), 327344.

Gallego, F. (2011). Skill premium in chile: Studying skill upgrading in the south. *World Development 68*(1), 29–51.

Goldin, C. and L. F. Katz (1998). The origins of technology-skill complementarity. *Quarterly Journal of Economics 113*(3), 693–732.

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

Griliches, Z. (1969). Capital-skill complementarity. *Review of Economics and Statistics 51*(4), 465–468.

Hatzichronoglou, T. (1997). Revision of the high-technology sector and product classification. OECD Science, Technology and Industry Working Papers.

Krueger, A. B. (1993). How computers have changed the wage structure: Evidence from microdata, 1984-1989. *Quarterly Journal of Economics 108*(1), 33–60.

Krusell, P., L. E. Ohanian, J.-V. Ríos-Rull, and G. L. Violante (2000). Capital-skill complementarity and inequality: A macroeconomic analysis. *Econometrica 68*(5), 1029–1053.

Levinsohn, J. (1999). Employment responses to international liberalization in Chile. *Journal of International Economics 47*(2), 321–344.

Levinsohn, J. and A. Petrin (2003). Estimating production functions using inputs to control for unobservables. *Review of Economic Studies 70*(2), 317–341.

Liu, L. (1993). Entry-exit, learning, and productivity change evidence from Chile. *Journal of Development Economics 42*(2), 217–242.

Oulton, N. and S. Srinivasan (2003). Capital stocks, capital services, and depreciation: an integrated framework. Bank of England Working Paper No. 192.

Papageorgiou, C. and V. Chmelarova (2005). Nonlinearities in capital-skill complementarity. *Journal of Economic Growth 10*(1), 59–89.

Parro, F. (Forthcoming). Capital-skill complementarity and the skill premium in a quantitative model of trade. *American Economic Journal: Macroeconomics*.

Pavcnik, N. (2002). Trade liberalization, exit, and productivity improvement: Evidence from Chilean plants. *Review of Economic Studies 69*(1), 245–276.

Polgreen, L. A. and P. Silos (2008). Capital-skill complementarity and inequality: A sensitivity analysis. *Review of Economic Dynamics 11*(2), 302–313.

Tybout, J., J. de Melo, and V. Corbo (1991). The effects of trade reforms on scale and technical efficiency: New evidence from Chile. *Journal of International Economics 31*(3-4), 231–250.

Uzawa, H. (1962). Production functions with constant elasticities of substitution. *Review of Economic Studies 29*(4), 291–299.

Wooldridge, J. M. (2003). *Econometric Analysis of Cross Section and Panel Data*. Massachusetts: The MIT Press.

Yasar, M. and C. J. M. Paul (2008). Capital-skill complementarity, productivity and wages: Evidence from plant-level data for a developing country. *Labour Economics 15*(1), 1–17.

A Figures and Tables

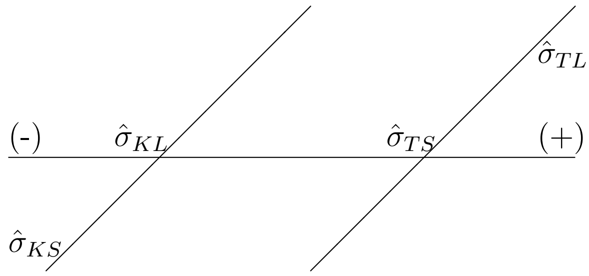


Figure 1: Augmenting effect when $\hat{\sigma}_{TS} > \hat{\sigma}_{KL}$

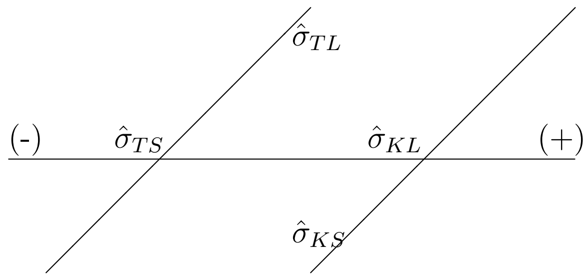
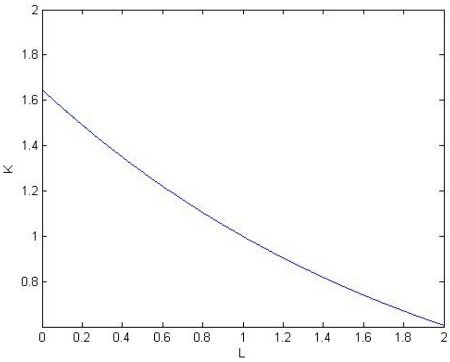
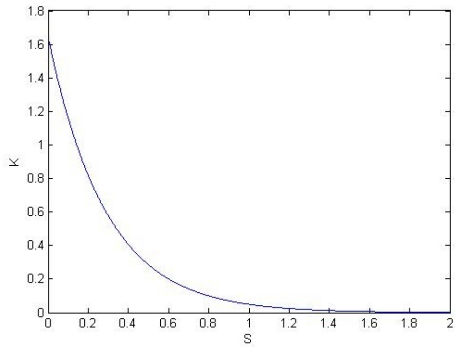


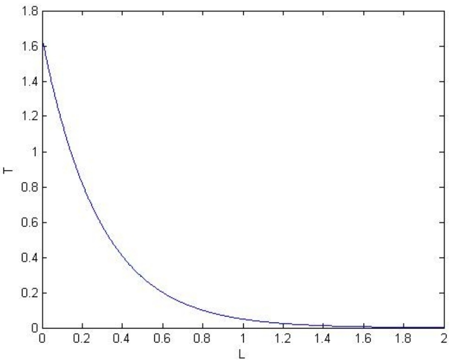
Figure 2: Ambiguous effect when $\hat{\sigma}_{TS} < \hat{\sigma}_{KL}$



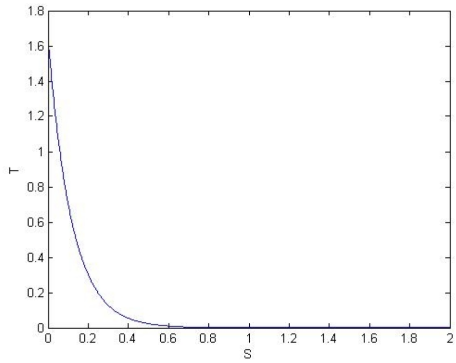
(a) Non-technological capital and unskilled labor



(b) Non-technological capital and skilled labor



(c) Technological capital and unskilled labor



(d) Technological capital and skilled labor

Figure 3: Capital and labor isoquants

Table 1: Groups of Industries

ISIC	Industry
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 (1) for the Aggregate Specification

	s_L	s_S
$\ln(L/Z)$	0.0566	-0.0396
	(0.000662)***	(0.000533)***
$\ln(S/Z)$	-0.0396	0.0621
	(0.000533)***	(0.000720)***
β	0.466	0.429
	(0.00274)***	(0.00274)***
Observations	4,500	4,500
R-squared	0.635	0.654

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

Table 3: Elasticities of Substitution for the Aggregate Specification

	Mean	95% Confidence Interval	
$\hat{\sigma}_{ZL}$	0.8034	0.7873	0.8177
$\hat{\sigma}_{ZS}$	0.6784	0.6545	0.7012
$\hat{\sigma}_{LS}$	0.7528	0.7456	0.7593
$\hat{\sigma}_{ZZ}$	-3.0826	-3.2176	-2.9569
$\hat{\sigma}_{LL}$	-0.9608	-0.998	-0.9268
$\hat{\sigma}_{SS}$	-1.3000	-1.3451	-1.2554

Table 4: Coefficients of Equation (1) for the Disaggregate Specifications

	s_L	s_S	s_T
Specification 1			
$\ln(L/K)$	0.0566	-0.0396	-0.000413
	(0.000664)***	(0.000534)***	(0.0000690)***
$\ln(S/K)$	-0.0396	0.0622	-0.000604
	(0.000534)***	(0.000722)***	(0.0000853)***
$\ln(T/K)$	-0.000413	-0.000604	0.00130
	(0.0000690)***	(0.0000853)***	(0.0000731)***
β	0.462	0.423	0.0128
	(0.00278)***	(0.00280)***	(0.000716)***
Specification 2			
$\ln(L/K)$	0.0566	-0.0396	-0.000405
	(0.000664)***	(0.000534)***	(0.0000689)***
$\ln(S/K)$	-0.0396	0.0622	-0.000585
	(0.000534)***	(0.000722)***	(0.0000849)***
$\ln(T/K)$	-0.000405	-0.000585	0.00127
	(0.0000689)***	(0.0000849)***	(0.0000726)***
β	0.462	0.423	0.0124
	(0.00278)***	(0.00280)***	(0.000705)***
Specification 3			
$\ln(L/K)$	0.0566	-0.0396	-0.000447
	(0.000663)***	(0.000534)***	(0.0000658)***
$\ln(S/K)$	-0.0396	0.0622	-0.000662
	(0.000534)***	(0.000720)***	(0.0000816)***
$\ln(T/K)$	-0.000447	-0.000662	0.00175
	(0.0000658)***	(0.0000816)***	(0.0000961)***
β	0.463	0.424	0.0115
	(0.00274)***	(0.00274)***	(0.000590)***
Specification 4			
$\ln(L/K)$	0.0574	-0.0417	-0.0105
	(0.000657)***	(0.000534)***	(0.000434)***
$\ln(S/K)$	-0.0417	0.0617	-0.0138
	(0.000534)***	(0.000707)***	(0.000480)***
$\ln(T/K)$	-0.0105	-0.0138	0.0284
	(0.000434)***	(0.000480)***	(0.000562)***
β	0.451	0.405	0.0983
	(0.00252)***	(0.00243)***	(0.00187)***

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

Table 5: Elasticities of Substitution for the Disaggregate Specifications

	Specification 1	Specification 2	Specification 3	Specification 4
$\hat{\sigma}_{KL}$	0.8067	0.8066	0.8059	0.8102
	[0.7922 0.8207]	[0.7921 0.8207]	[0.7914 0.8198]	[0.7903 0.8308]
$\hat{\sigma}_{KS}$	0.6831	0.6829	0.6818	0.7214
	[0.659 0.7065]	[0.6588 0.7064]	[0.6579 0.7052]	[0.6903 0.7479]
$\hat{\sigma}_{TL}$	0.4077	0.4356	0.6956	0.8042
	[0.3067 0.4974]	[0.3398 0.5240]	[0.6465 0.7415]	[0.7864 0.8203]
$\hat{\sigma}_{TS}$	-0.0767	-0.0153	0.4409	0.6814
	[-0.2984 0.1306]	[-0.2233 0.1754]	[0.3492 0.5180]	[0.6574 0.7042]
$\hat{\sigma}_{KT}$	0.0974	0.1379	-0.0250	0.4280
	[-0.6941 0.6542]	[-0.6010 0.6551]	[-0.5688 0.3414]	[0.3065 0.5311]
$\hat{\sigma}_{LS}$	0.7528	0.7528	0.7528	0.7499
	[0.7463 0.7594]	[0.7463 0.7593]	[0.7457 0.7595]	[0.7432 0.7561]
$\hat{\sigma}_{KK}$	-3.1407	-3.1411	-3.1446	-11.3211
	[-3.2647 -3.0092]	[-3.2652 -3.0095]	[-3.2833 -3.0057]	[-11.8886 -10.7647]
$\hat{\sigma}_{TT}$	-118.7888	-142.7035	-142.2497	-5.4338
	[-232.3992 -33.2848]	[-256.0731 -53.6016]	[-190.5978 -89.3749]	[-5.6894 -5.1749]
$\hat{\sigma}_{LL}$	-0.9599	-0.9599	-0.9620	-0.9251
	[-0.9945 -0.9271]	[-0.9944 -0.9271]	[-0.9940 -0.9287]	[-0.9605 -0.8926]
$\hat{\sigma}_{SS}$	-1.2961	-1.2962	-1.2990	-1.2627
	[-1.3465 -1.2539]	[-1.3466 -1.2540]	[-1.3465 -1.2540]	[-1.3094 -1.2166]
$\hat{\sigma}_{KL}/\hat{\sigma}_{KS}$	1.18	1.18	1.18	1.12
$\hat{\sigma}_{TL}/\hat{\sigma}_{TS}$	-5.32	-28.47	1.58	1.18
$\hat{\sigma}_{KS}/\hat{\sigma}_{TL}$	1.68	1.57	0.98	0.90
$\hat{\sigma}_{KL}/\hat{\sigma}_{TS}$	-10.52	-52.72	1.83	1.19

95% bootstrap confidence intervals in square brackets.

Table 6: Industry Group Elasticities of Substitution for the Disaggregate Specifications

Group	$\hat{\sigma}_{KL}$	$\hat{\sigma}_{KS}$	$\hat{\sigma}_{TL}$	$\hat{\sigma}_{TS}$
Specification 1				
High	0.7542	0.5311	0.7648	0.1717
	[0.6864 0.8134]	[0.4233 0.6168]	[0.6455 0.8842]	[-0.0849 0.4014]
Medium	0.8349	0.6516	0.5192	-0.6346
	[0.8108 0.8583]	[0.6000 0.6969]	[0.3555 0.6591]	[-1.1197 -0.223]
Low	0.7954	0.7136	0.2267	-0.0108
	[0.7760 0.8153]	[0.6826 0.7413]	[0.0648 0.3856]	[-0.3046 0.2672]
Specification 2				
High	0.7541	0.5311	0.7944	0.2376
	[0.6861 0.8133]	[0.4235 0.6168]	[0.6778 0.9112]	[0.0024 0.4473]
Medium	0.8348	0.6515	0.5301	-0.5471
	[0.8107 0.8582]	[0.6000 0.6969]	[0.3683 0.6654]	[-1.0042 -0.1508]
Low	0.7953	0.7133	0.2671	0.0438
	[0.7759 0.8153]	[0.6820 0.7412]	[0.1133 0.4223]	[-0.2315 0.2884]
Specification 3				
High	0.7526	0.5312	0.7962	0.4241
	[0.6856 0.8129]	[0.4177 0.6194]	[0.6801 0.8914]	[0.2805 0.5608]
Medium	0.8347	0.6506	0.7581	0.2951
	[0.8095 0.8562]	[0.5922 0.6932]	[0.6711 0.8342]	[0.0712 0.4691]
Low	0.7943	0.712	0.6177	0.4623
	[0.7738 0.8126]	[0.6837 0.7390]	[0.5359 0.7005]	[0.3285 0.5683]
Specification 4				
High	0.7641	0.6602	0.7815	0.5503
	[0.6880 0.8318]	[0.5417 0.7545]	[0.7189 0.8363]	[0.4515 0.6384]
Medium	0.8321	0.7235	0.8351	0.6103
	[0.7857 0.8735]	[0.6639 0.7763]	[0.8052 0.8632]	[0.5581 0.6582]
Low	0.7955	0.7310	0.7886	0.7213
	[0.7707 0.8200]	[0.6943 0.7652]	[0.7676 0.8083]	[0.6936 0.7492]

95% bootstrap confidence intervals in square brackets.

Table 7: Check of Robustness for Table 3 Results

	Mean	95% Confidence Interval	
$\hat{\sigma}_{ZL}$	0.8165	0.8015	0.8303
$\hat{\sigma}_{ZS}$	0.7037	0.6808	0.7244
$\hat{\sigma}_{LS}$	0.7503	0.7433	0.7568
$\hat{\sigma}_{ZZ}$	-3.1592	-3.2959	-3.0308
$\hat{\sigma}_{LL}$	-0.9645	-1.0009	-0.9308
$\hat{\sigma}_{SS}$	-1.3107	-1.3559	-1.2665

Table 8: Check of Robustness for Table 5 Results

	Specification 1	Specification 2	Specification 3	Specification 4
$\hat{\sigma}_{KL}$	0.8197	0.8196	0.8188	0.8200
	[0.8055 0.8333]	[0.8053 0.8332]	[0.8048 0.8313]	[0.8003 0.8401]
$\hat{\sigma}_{KS}$	0.7081	0.7080	0.7075	0.7373
	[0.6855 0.7297]	[0.6853 0.7295]	[0.6853 0.7287]	[0.7069 0.7641]
$\hat{\sigma}_{TL}$	0.3760	0.4129	0.7117	0.8256
	[0.2640 0.4782]	[0.3123 0.5077]	[0.6619 0.7591]	[0.8100 0.8413]
$\hat{\sigma}_{TS}$	-0.0300	0.0345	0.4494	0.7172
	[-0.2773 0.1973]	[-0.2067 0.2460]	[0.3416 0.5342]	[0.6935 0.7402]
$\hat{\sigma}_{KT}$	-0.0953	-0.0304	-0.1054	0.3945
	[-0.9030 0.4994]	[-0.7739 0.5276]	[-0.7414 0.2996]	[0.2775 0.4982]
$\hat{\sigma}_{LS}$	0.7505	0.7504	0.7503	0.7467
	[0.7439 0.757]	[0.7439 0.7570]	[0.7432 0.7568]	[0.7402 0.7525]
$\hat{\sigma}_{KK}$	-3.2159	-3.2165	-3.2212	-11.4259
	[-3.3416 -3.089]	[-3.3424 -3.0897]	[-3.3621 -3.0893]	[-11.9981 -10.8818]
$\hat{\sigma}_{TT}$	-95.6004	-126.4567	-140.7711	-5.6104
	[-205.7389 -17.6514]	[-236.2533 -47.2766]	[-190.4369 -84.5678]	[-5.8737 -5.3447]
$\hat{\sigma}_{LL}$	-0.9635	-0.9635	-0.9657	-0.9294
	[-0.9984 -0.9301]	[-0.9983 -0.9301]	[-0.9971 -0.9331]	[-0.9643 -0.8971]
$\hat{\sigma}_{SS}$	-1.3068	-1.3069	-1.3096	-1.2729
	[-1.3549 -1.2649]	[-1.3550 -1.2650]	[-1.3568 -1.2639]	[-1.3192 -1.2268]
$\hat{\sigma}_{KL}/\hat{\sigma}_{KS}$	1.16	1.16	1.16	1.11
$\hat{\sigma}_{TL}/\hat{\sigma}_{TS}$	-12.53	11.97	1.58	1.15
$\hat{\sigma}_{KS}/\hat{\sigma}_{TL}$	1.88	1.71	0.99	0.89
$\hat{\sigma}_{KL}/\hat{\sigma}_{TS}$	-27.32	23.76	1.82	1.14

95% bootstrap confidence intervals in square brackets.

Table 9: Check of Robustness for Table 6 Results

Group	$\hat{\sigma}_{KL}$	$\hat{\sigma}_{KS}$	$\hat{\sigma}_{TL}$	$\hat{\sigma}_{TS}$
Specification 1				
High	0.7880	0.5587	0.7132	0.2406
	[0.7188 0.8504]	[0.4546 0.6418]	[0.5742 0.8830]	[0.0267 0.4466]
Medium	0.8488	0.6734	0.4228	-0.4779
	[0.8229 0.8724]	[0.6189 0.7153]	[0.2278 0.5764]	[-0.9488 -0.0639]
Low	0.8101	0.7465	0.2201	0.0176
	[0.7931 0.8281]	[0.7205 0.7705]	[0.0392 0.3937]	[-0.3305 0.3454]
Specification 2				
High	0.7878	0.5586	0.7577	0.3019
	[0.7185 0.8504]	[0.4542 0.6419]	[0.6216 0.9088]	[0.1097 0.4935]
Medium	0.8488	0.6733	0.4430	-0.3938
	[0.8228 0.8724]	[0.6188 0.7153]	[0.2442 0.5917]	[-0.8563 0.0058]
Low	0.8100	0.7463	0.2649	0.0780
	[0.7929 0.8281]	[0.7202 0.7704]	[0.0935 0.4241]	[-0.2509 0.373]
Specification 3				
High	0.7877	0.5601	0.8327	0.4175
	[0.7215 0.8503]	[0.4548 0.6454]	[0.7276 0.9418]	[0.2547 0.567]
Medium	0.8487	0.6717	0.7547	0.3593
	[0.8241 0.8705]	[0.6139 0.7153]	[0.6662 0.8364]	[0.1563 0.5235]
Low	0.8092	0.7458	0.6270	0.4662
	[0.7909 0.8255]	[0.7205 0.7696]	[0.5425 0.7101]	[0.3127 0.5791]
Specification 4				
High	0.7974	0.6821	0.8428	0.5904
	[0.7129 0.8721]	[0.5686 0.777]	[0.7839 0.9019]	[0.4916 0.6767]
Medium	0.8428	0.7181	0.8580	0.6456
	[0.7969 0.8854]	[0.6582 0.7743]	[0.8285 0.8872]	[0.5936 0.6932]
Low	0.8078	0.7571	0.8110	0.7681
	[0.7826 0.8317]	[0.7189 0.7913]	[0.7909 0.83]	[0.7399 0.794]

95% bootstrap confidence intervals in square brackets.