CAPITAL-SKILL COMPLEMENTARITY? EVIDENCE FROM A PANEL OF COUNTRIES*

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ABSTRACT

Since Griliches (1969), researchers have been intrigued by the idea that physical capital and skilled labor are relatively more complementary than physical capital and unskilled labor. This capital–skill complementarity hypothesis has received renewed attention recently, as researchers have suggested that this phenomenon might account for rising wage inequality between skilled and unskilled workers in several developed countries. In this paper we consider the cross–country evidence for capital–skill complementarity using a time–series, cross–section panel of 73 developed and less developed countries over a 25 year period. In particular, we focus on three empirical issues. First, what is the best specification of the aggregate production technology to address the capital–skill complementarity hypothesis. Second, how should we measure skilled labor? Finally, is there any cross–country evidence in support of the capital–skill complementarity hypothesis? Our main finding is that we are unable to reject the null hypothesis of no capital–skill complementarity using our panel data set.

KEYWORDS: Input Complementarities, Production Function Estimation

JEL Classification Numbers: O40, O47.

1 Introduction

Over 30 years ago, Griliches (1969) provided evidence from U.S. manufacturing data suggesting that capital and skilled labor are relatively more complementary as inputs than are capital and unskilled labor. Griliches referred to this finding as the "capital–skill complementarity" hypothesis. Griliches' hypothesis has received renewed attention lately, as the U.S. and other developed nations have invested heavily in "skill–biased" information technology and this development appears to have coincided with a rise in the wages earned by skilled workers relative to the wages of unskilled workers. Indeed, belief in the existence of capital–skill complementarity is so strong that some researchers have suggested modifying the standard neoclassical production technology to account for this phenomenon in addressing questions of economic growth, trade and inequality (see, e.g. Stokey (1996), and Krusell et al. (2000)).

Goldin and Katz (1998) have recently reminded us that physical capital and skilled labor have not always been viewed as relative complements. For example, they note that in an earlier era, the transformation from skilled artisan shops to factories involved the substitution of physical capital and/or unskilled labor for highly skilled labor – precisely the opposite of what is hypothesized to be happening today. Goldin and Katz's findings suggest that capital–skill complementarities, to the extent they exist, may only be transitory phenomena that change with changes in production processes. As countries progress through various stages of development, skilled labor may change from being relatively more substitutable with capital and unskilled labor to being highly complementary to these two inputs. It therefore seems important to consider the evidence for capital–skill complementarity over long periods of time and across countries at different stages of development. The aim of this paper is to conduct such an exercise. In particular we examine the evidence for capital–skill complementarity using a panel data set of 73 countries over the period 1965–1990.

Not surprisingly, since Griliches (1969), the capital–skill complementarity hypothesis has attracted the attention of many researchers who have mainly used cross–sectional manufacturing data for a single (typically) developed country to test this hypothesis. Hamermesh (1993) assesses the findings from most of these studies and concludes that there "may be" capital–skill complementarity. However, he cautions that "many of the studies that disaggregate the work force by demographic group exclude capital as a productive input due to the difficulty of generating satisfactory data on capital stocks in the cross sections examined" (Hamermesh (1993) p. 113). For example, in the original Griliches (1969) study, the assumption of perfectly competitive markets allows gross rates of return to proxy for the marginal product of capital and capture variations in the stock of capital. By contrast, in this paper, we make use of the Penn World Tables–Version 5.6 dataset on investment rates across countries to construct physical capital stocks. We examine the capital–skill complementarity hypothesis *directly*, without resorting to assumptions of perfectly competitive markets, by estimating the parameters of various different specifications of an aggregate production function.[1] While the competitive markets assumption may seem reasonable for developed countries, it may be less reasonable for developing countries where factors may be less mobile and markets less complete.

Hamermesh (1993) also notes the difficulties that earlier studies had in using occupational data to differentiate between skilled and unskilled workers. In this paper, we follow the tradition in the macro–growth literature and differentiate labor according to educational attainment levels using the recent Barro and Lee (2000) dataset. In particular, we consider four alternative proxies for skilled labor ranging from workers possessing some secondary education to workers who have completed post secondary education; for each proxy, the remainder of the labor force is regarded as unskilled. We also examine what happens when we augment our labor data with data on returns to schooling (earnings) in an effort to account for disparities in efficiency units across workers *within* the class of workers regarded as skilled or unskilled. Our analysis of several different classifications and measures of skilled and unskilled labor is another novel feature of this study; in prior studies involving skilled and unskilled labor, a single educational threshold has been chosen to divide workers into skilled and unskilled classes without much consideration being given to the empirical relevance of the threshold choice.

International examinations of the capital–skill complementarity hypothesis have been conducted by Fallon and Layard (1975), Berman et al. (1998) and Flug and Hercowitz (2000). Our approach is most closely related to the Fallon and Layard (1975) study; the Berman et al. and Flug and Hercowitz studies do not employ aggregate production functions to test capital–skill complementarity across countries. Fallon and Layard used data pieced together for 9 developed and 13 less developed countries for a single year, 1963, to estimate reduced form equations derived from two–level CES production functions that allowed for there to be differences in the elasticity of substitution

[1]The methodology used in this paper follows Duffy and Papageorgiou (2000) who investigate a general two–factor CES aggregate specification in which output is generated using physical capital and labor or human capital adjusted labor serving as inputs.

between capital and skilled labor and the elasticity of substitution between capital and unskilled labor. At the economy–wide level, they find "mild" (though statistically insignificant) evidence in favor of the capital–skill complementarity hypothesis. In this paper, we also make use of the two–level CES production function specification that Fallon and Layard advocate. However, since we use nonlinear estimation methods that were not feasible at the time of the Fallon and Layard study, we do not need to follow Fallon and Layard further in assuming perfectly competitive markets so that factor price data (reflecting marginal products under perfect competition) can be used to estimate linear reduced form equations. Furthermore, we use data for many more countries, 73, and there is also a time dimension to our panel dataset that was missing from Fallon and Layard's study. Specifically, for each of the 73 countries, we have 6 annual observations, spaced five years apart: 1965,1970,...,1990 (a total of 438 observations). Finally, we report the results of Monte Carlo experiments that demonstrate the accuracy of the nonlinear estimation algorithm that we employ for small samples sizes comparable to those we examine.

Our analysis thus allows for a clearer and more convincing assessment of whether the capital–skill complementarity hypothesis is common to many countries over some length of time. If it is, then we may profit from modifying our specifications of the aggregate production technology to account for capital–skill complementarity. On the other hand, if the capital–skill complementarity hypothesis is not a robust phenomenon then it is not clear that this hypothesis is important to understanding economic growth patterns across countries, at least at the aggregate level that we examine. In addition, our findings may serve to stimulate alternative explanations for rising wage and income inequality that stress other factors, for example institutional changes or government interventions that may (or may not) be country–specific.

2 Examining The Case for Capital Skill Complementarity using Aggregate Production Functions

The capital–skill complementarity hypothesis states that physical capital is more complementary to skilled labor than to unskilled labor. More formally, suppose aggregate output, Y, is given by a three–factor production technology $Y = F(K, S, N)$, where K denotes the physical capital stock, S denotes the quantity of skilled labor and N denotes the quantity of unskilled labor. Denote by $\sigma_{i,j}$ the elasticity of substitution (ES) between inputs i and j.

Capital–skill complementarity holds if $\sigma_{K,N} > \sigma_{K,S} \Leftrightarrow \frac{\partial}{\partial K}\left(\frac{F_S}{F_N}\right) > 0$. To show that this is true we use the following definitions of the elasticity of substitution:

$$\begin{aligned}
\sigma_{K,N} &= El_{R_{K,N}}(K/N) = \frac{R_{K,N}}{K/N}\frac{\partial(K/N)}{\partial(R_{K,N})}, \\
\sigma_{K,S} &= El_{R_{K,S}}(K/S) = \frac{R_{K,S}}{K/S}\frac{\partial(K/S)}{\partial(R_{K,S})},
\end{aligned}$$

where $El_x(z)$ denotes the elasticity of z with respect to x (the percentage change in z given a percentage change in x), $R_{i,j} = \frac{F_j}{F_i}$ is the Marginal Rate of Technical Substitution (MRTS) between inputs i and j. Starting from the inequality $\sigma_{K,N} > \sigma_{K,S}$ and manipulating the ES definitions we obtain that

$$\frac{\partial(F_S/F_K)}{\partial(K/S)}\frac{1}{SF_S} > \frac{\partial(F_N/F_K)}{\partial(K/N)}\frac{1}{NF_N}.$$

Finally, using the chain rule one can show that $\frac{F_{S,K}}{F_S} > \frac{F_{N,K}}{F_N}$, where $F_{i,j}$ is the cross–partial derivative. It is then easily shown that

$$\frac{F_{S,K}}{F_S} > \frac{F_{N,K}}{F_N} \Leftrightarrow \frac{\partial}{\partial K}\left(\frac{F_S}{F_N}\right) > 0.$$

In order to assess the extent of capital skill complementarity, we must work with a functional form that is general enough to accommodate different elasticities of substitution. For example, the relatively general CES form for $F(K,S,N)$,

$$Y = A\left[aK^\rho + bS^\rho + cN^\rho\right]^{\frac{1}{\rho}},$$

where $a+b+c = 1$ and $\rho \leq 1$, implies that the elasticity of substitution between any two inputs, $\sigma_{i,j}$ for $i,j \in \{K,S,N\}$, is constant and equal to $\frac{1}{1-\rho}$. To allow for different elasticities of substitution between any two inputs requires a two–level CES form á la Fallon and Layard (1975). The two most interesting versions of this two–level CES form for the purposes of testing the capital–skill complementarity hypothesis are

$$Y = A\left[a[bK^\theta + (1-b)S^\theta]^{\rho/\theta} + (1-a)N^\rho\right]^{1/\rho},\ \sigma_{K,S} = \frac{1}{1-\theta}, \sigma_{K,N} = \sigma_{N,S} = \frac{1}{1-\rho}, \quad (1)$$

$$Y = A\left[a[bK^\theta + (1-b)N^\theta]^{\rho/\theta} + (1-a)S^\rho\right]^{1/\rho},\ \sigma_{K,N} = \frac{1}{1-\theta}, \sigma_{K,S} = \sigma_{N,S} = \frac{1}{1-\rho}, \quad (2)$$

where A is a positive technological parameter, a, b are distribution parameters and θ, $\rho \leq 1$ are the elasticity of substitution parameters (θ, $\rho = 1$ imply perfect substitutability, θ, $\rho = 0$ imply the

Cobb–Douglas specification, and θ, $\rho = -\infty$ imply perfect complementarity). Using the two–level CES technology of equation (1)[2] implies that capital–skill complementarity hypothesis holds iff $\rho > \theta$ [$\rho < \theta$].[2] Even though the two specifications are obviously very similar, they differ in one important way. Notice that where (1) implies that the elasticity of substitution between K and N, and N and S are the same (i.e. $\sigma_{K,N} = \sigma_{N,S}$), equation (2) implies that the elasticity of substitution between K and S, and N and S are the same (i.e. $\sigma_{K,S} = \sigma_{N,S}$).

Though further disaggregation is possible, e.g. through the use of a translog specification (see, e.g. Bergström and Panas (1992)), we focus on these two–level CES specifications as they are the ones that have been used in the recent literature examining the consequences of the capital–skill complementarity hypothesis. For example, Fallon and Layard (1975) and Caselli and Coleman (2000) both prefer to work with specification (1). Krusell et al. (2000) consider an expanded version of specification (1)

$$Y = AK_s^{\alpha}\left[a[bK_e^{\theta} + (1-b)S^{\theta}]^{\rho/\theta} + (1-a)N^{\rho}\right]^{\frac{1-\alpha}{\rho}},$$

where K_s represents the stock of capital structures, and K_e represents the stock of capital equipment. While we would like to estimate such a specification, we lack the requisite data on capital structures and capital equipment for all of the countries in our sample.[3]

Stokey (1996), on the other hand, has proposed a more restrictive version of specification (2):

$$Y = A[bK^{\theta} + (1-b)N^{\theta}]^{\gamma/\theta}\tilde{S}^{(1-\gamma)}. \tag{3}$$

Here $\tilde{S} = S + qN$ represents "mental effort", $q < 1$ is the relative efficiency of unskilled labor in contributing to mental effort, and $1-\gamma$ is the share of output that accrues to $\tilde{S}$. Equation (3) is clearly a restricted form of (2) as it requires finding that estimates of ρ are not significantly different from zero. Conditional on this finding capital–skill complementarity holds if $0 < \theta \leq 1$.[4]

[2] Fallon and Layard show that after some algebra the specification (1) implies

$$\frac{F_{S,K}}{F_S} - \frac{F_{N,K}}{F_N} > 0 \Leftrightarrow a(1-a)b(1-b)A^{2\rho}Y^{2(1-\rho)}K^{\theta-1}S^{\theta-1}N^{\rho-1}[bK_{it}^{\theta} + (1-b)S_{it}^{\theta}]^{(\rho-2\theta)/\theta}(\rho-\theta) > 0$$
$$\Rightarrow (\rho-\theta) > 0.$$

[3] Krusell et al. (2000) only consider the U.S. economy, for which such data are available.

[4] Following Stokey's formulation, the restricted version of the two–level CES specification (1) is:

$$Y = A[bK^{\theta} + (1-b)S^{\theta}]^{\gamma/\theta}N^{1-\gamma},$$

and capital–skill complementarity holds if $\theta < 0$.

Goldin and Katz (1998) start off with the two–level CES specification (1) but further specialize it to the case where 1) $\theta \to -\infty$ and 2) $\rho \to 0$. This is even more restrictive than Stokey (1996), since it implies, as in Stokey, that final output Y has the Cobb–Douglas form but it further requires that the K–S aggregate, which Goldin and Katz refer to as K^*, have the Leontief form:

$$Y = A\left[\left(\min\left[bK, (1-b)S\right]\right)^{\gamma} N^{1-\gamma}\right].$$

In this case, since $\sigma_{K,S} = 0 < 1$ and $\sigma_{K^*,N} = 1$, the authors are making the empirically testable assumption that $\sigma_{K,S} < \sigma_{K^*,N}$. Their aim is to show that if technology changes, represented by a change in A, then it need not be the case that the relative demand for skilled labor increases. As A increases, less is needed of both the K^* aggregate and N to produce the same level of output.

While there is some supporting evidence for the capital–skill complementarity hypothesis using alternative data sets and methodologies as noted in the introduction, the hypothesis has not been tested 1) using aggregate production function specifications directly or 2) using a cross–section, time–series panel dataset.[5] The latter point is particularly relevant in growth models that use the aggregate production functions motivated by the supposed existence of capital–skill complementarities. In addition, as our literature review suggests, there is no consensus yet on the appropriate functional form to use to capture capital–skill complementarity. Our estimation exercise, to which we now turn, sheds some light on this question as well.

3 Estimation Procedures and Specifications

The various versions of the two–level CES production technologies presented above are highly nonlinear and therefore, nonlinear estimation methods (in particular NLLS and GMM) will be used to obtain estimates of ρ and θ. These computationally intensive methods were not feasible when Fallon and Layard (1975) first proposed estimation of production function specifications, and consequently, they had to resort to estimation of restrictive linear specifications as noted in the introduction.

[5] Flug and Hercowitz (2000) who investigate the related idea of an equipment–skill complementarity hypothesis do use international panel data from 35 countries. However, they do not estimate production functions directly as we do here. Instead, they use a linear regression model of wage and unemployment ratios of skilled to unskilled workers. Their results suggest that investment in equipment raises the relative demand for skilled workers.

3.1 The Two–Level CES Specifications

The two–level CES production function equations that will be empirically tested are:

$$Y_{it} = A_{i0}\left[a[bK_{it}^{\theta} + (1-b)S_{it}^{\theta}]^{\rho/\theta} + (1-a)N_{it}^{\rho}\right]^{1/\rho} e^{\lambda t+\varepsilon_{it}}, \tag{4}$$

$$Y_{it} = A_{i0}\left[a[bK_{it}^{\theta} + (1-b)N_{it}^{\theta}]^{\rho/\theta} + (1-a)S_{it}^{\rho}\right]^{1/\rho} e^{\lambda t+\varepsilon_{it}}, \tag{5}$$

where i denotes the country, t denotes the year and ε is the error term. We assume exogenous, Hicks neutral technological growth. In particular, we assume A is growing at the rate λ, with A_{i0} representing the initial ($t = 0$) value of A for country i.[6] Notice that model specification (4) corresponds to the first version of the two–level CES form, equation (1), and model specification (5) corresponds to the second version of the two–level CES form, equation (2). While it is possible to linearize equations (4–5), the resulting equations are complicated and impossible to estimate.[7] The only remaining viable option is nonlinear estimation and that is how we proceed.

In using panel data for our estimation exercise, we must confront two potential econometric problems. First, there is the problem of unmodeled, country specific *fixed–effects*, due for example, to differences in technology, culture or geography (see, e.g. Islam (1995)). Assuming these factors are time invariant, we can resolve the fixed effects problem by supposing that the error term, $\varepsilon_{it} = \eta_i + \epsilon_{it}$, where η_i represents the country specific fixed factors in country i. Under this assumption, log differencing (4) and (5) yields

$$\log\left(\frac{Y_{it}}{Y_{i,t-1}}\right) = \lambda + \frac{1}{\rho}\log\frac{\left[a[bK_{it}^{\theta} + (1-b)S_{it}^{\theta}]^{\rho/\theta} + (1-a)N_{it}^{\rho}\right]}{\left[a[bK_{i,t-1}^{\theta} + (1-b)S_{i,t-1}^{\theta}]^{\rho/\theta} + (1-a)N_{i,t-1}^{\rho}\right]} + \epsilon_{it} - \epsilon_{i,t-1}, \tag{6}$$

$$\log\left(\frac{Y_{it}}{Y_{i,t-1}}\right) = \lambda + \frac{1}{\rho}\log\frac{\left[a[bK_{it}^{\theta} + (1-b)N_{it}^{\theta}]^{\rho/\theta} + (1-a)S_{it}^{\rho}\right]}{\left[a[bK_{i,t-1}^{\theta} + (1-b)N_{i,t-1}^{\theta}]^{\rho/\theta} + (1-a)S_{i,t-1}^{\rho}\right]} + \epsilon_{it} - \epsilon_{i,t-1}. \tag{7}$$

A second problem concerns the possible endogeneity of the input variables in our regression specifications, as emphasized by Caselli et al. (1996). We resolve this second problem by using a GMM, instrumental variables procedure to estimate the log–differenced model, where we use lagged values of the right hand side input variables as instruments.

[6] That is, $A_{it} = A_{i0}e^{\lambda t}$. In an interesting paper, Caselli and Coleman (2000) use a two–level CES specification in which they allow the efficiency parameters for the three different factors, unskilled labor, skilled labor and capital to differ from one another.

[7] Using a second order Taylor series expansion it is possible to obtain a linear approximation of the two–level CES specification. Unlike the linearized version of Stokey's formulation, discussed below (in footnote 9), the linearized approximation of the two–level CES specification (linearized around $\rho, \theta = 0$) contains a large number of linear parts with multiple coefficients that cannot be identified using standard linear estimation techniques.

3.2 CES–nested–in–Cobb–Douglas Specification

An alternative to the two–level CES specifications is the more restricted version of these specifications proposed by Stokey (1996) as given by equation (3). Our estimated version of Stokey's production function specification is of the following form:

$$Y_{it} = A_{i0}[bK_{it}^{\theta} + (1-b)N_{it}^{\theta}]^{\gamma/\theta} S_{it}^{1-\gamma} e^{\lambda t + \varepsilon_{it}}. \tag{8}$$

In (8), capital and unskilled workers are combined into an aggregate by a CES specification. The resulting aggregate measure is then combined with skilled labor using a Cobb–Douglas technology. Notice that our specification (8) is really a special case of (3) in that we assume that $q = 0$; this assumption implies that mental effort in the production process is exerted only by skilled workers.[8] The capital–skill complementarity would hold in this case if the elasticity of substitution between capital and unskilled workers is greater than unity, $\sigma_{K,N} = \frac{1}{1-\theta} > 1$ or $0 < \theta \leq 1$. Similarly, the restricted version of specification (1) that we will estimate is given by

$$Y_{it} = A_{i0}[bK_{it}^{\theta} + (1-b)S_{it}^{\theta}]^{\gamma/\theta} N_{it}^{1-\gamma} e^{\lambda t + \varepsilon_{it}}, \tag{9}$$

where the sufficient condition for capital–skill complementarity is reversed, $\sigma_{K,S} = \frac{1}{1-\theta} < 1$ or $\theta < 0$. We will refer to specifications (8–9) as the "CES–nested–in–Cobb–Douglas" specifications, and we will estimate them using nonlinear least squares.

As in the case of the general, two–level CES specifications, we also consider a log–difference version of the "CES–nested–in–Cobb–Douglass" specification that gets rid of country–specific fixed effects. Log–differencing (9) and (8) (note the change in order) we obtain the following two expressions:

$$\log\left(\frac{Y_{it}}{Y_{i,t-1}}\right) = \lambda + \frac{\gamma}{\theta}\log\frac{[bK_{it}^{\theta} + (1-b)S_{it}^{\theta}]}{[bK_{i,t-1}^{\theta} + (1-b)S_{i,t-1}^{\theta}]} + (1-\gamma)\log\left(\frac{N_{it}}{N_{i,t-1}}\right) + \epsilon_{it} - \epsilon_{i,t-1}, \tag{10}$$

$$\log\left(\frac{Y_{it}}{Y_{i,t-1}}\right) = \lambda + \frac{\gamma}{\theta}\log\frac{[bK_{it}^{\rho} + (1-b)N_{it}^{\theta}]}{[bK_{i,t-1}^{\theta} + (1-b)N_{i,t-1}^{\theta}]} + (1-\gamma)\log\left(\frac{S_{it}}{S_{i,t-1}}\right) + \epsilon_{it} - \epsilon_{i,t-1}. \tag{11}$$

We will estimate (10–11) using nonlinear least squares and using a GMM, instrumental variables procedure where lagged values of the right hand side variables are used as instruments.[9]

[8] There exists no empirical evidence on q (the contribution of unskilled labor to mental effort). Stokey (1996) simply assumes that $q = 0.25$ in order to keep the skill premium within a reasonable range in her calibration exercises.

[9] We note that it is possible to obtain a linearized version of the restricted "CES–nested–in–Cobb Douglas"

4 The Data

Our estimation requires data for real GDP (Y), the stock of physical capital (K), unskilled labor (N), and skilled labor (S). We obtain data for Y from the Penn World Tables v. 5.6 (PWT–5.6), and construct data for K using investment shares data from the PWT–5.6 and the perpetual inventory approach. Data for both Y and K are in constant U.S. dollars (1985 international prices). Since the data we use to construct the skilled labor proxies are only available every five years, our dataset consists of a number of annual observations (6) for each country, spaced five years apart. We construct four alternative proxies for skilled (unskilled) labor since it was not clear to us how skilled (unskilled) labor should be defined. Our four proxies for skilled labor are: workers who have completed a post–secondary (college) education (labeled $S1$), workers with some post–secondary education ($S2$), workers who have completed a secondary education ($S3$), and workers with some secondary education ($S4$). Our four proxies for skilled labor were constructed by multiplying enrollment rate data (from Barro and Lee (2000)) for each of the four different cut–off criteria by the size of the labor force in each country at each date in our sample. The remainder of the labor force (those not classified according to the definition of skilled labor ($S1$–$S4$) was regarded as unskilled labor, and was designated by $N1$, $N2$, $N3$ or $N4$, corresponding to the definition of skilled labor. The resulting dataset consists of 73 countries; for each country there are six annual observations of all input and output variables spaced five years apart starting in 1965 and ending in 1990 (438 observations). We choose to work with a large panel of countries, rather than estimating production functions for individual countries as we have only six observations per country and the CES specifications involve as many as six parameters.

Since workers with a college degree may contribute more efficiency units than workers with a secondary education only, the proxies we used for skilled (unskilled) labor could suffer from

specification. Divide the left and right hand sides of (9) by N_{it}, and the left and right hand sides of (8) by S_{it}. Log–linearizing the resulting equations around $\theta = 0$ gives respectively:

$$\log y_{it} = \log A_{i0} + \lambda t + \gamma b \log k_{it} + \gamma(1-b)\log s_{it} + 1/2\gamma b(1-b)\theta\left(\log\frac{k_{it}}{s_{it}}\right)^2 + \varepsilon_{it},$$

where $y = \frac{Y}{N}$, $k = \frac{K}{N}$, $s = \frac{S}{N}$ and

$$\log y_{it} = \log A_{i0} + \lambda t + \gamma b \log k_{it} + \gamma(1-b)\log n_{it} + 1/2\gamma b(1-b)\theta\left(\log\frac{k_{it}}{n_{it}}\right)^2 + \varepsilon_{it},$$

where $y = \frac{Y}{S}$, $k = \frac{K}{S}$, $n = \frac{N}{S}$. We obtained estimates from these linear specifications using OLS with time and fixed effects and instrumental variables but found that they did not change the main conclusions we obtained from the more general nonlinear specifications. We therefore chose to omit these findings from the paper.

aggregation problems, for example, when skilled labor is defined as those who have completed a secondary education ($S3$). In an effort to address this problem, we follow Caselli and Coleman (2000) and employ additional data on returns to schooling to weight individuals *within* our two divisions of the labor force into skilled or unskilled labor. We will refer to this dataset as the "weighted" labor data, to differentiate it from the data where returns to schooling data are not used in the construction of proxies for skilled and unskilled labor (the "unweighted" labor data). While adjusting the skilled/unskilled labor proxies to account for returns to schooling may seem quite reasonable, it comes at the cost of drastically reducing our sample size from 73 to 49 countries (from 438 to 294 observations) due to the lack of data on returns to schooling for 24 countries. We will return to this issue later in the paper.[10] Because of this data constraint, we report results for both the larger, unweighted labor dataset and the smaller weighted labor dataset.

The appendix provides further details concerning the sources and construction of the data used in this paper as well as a table reporting the mean values of Y, K, $S1$ and $N1$ for each country in the sample.

5 Results

Our results consist of several sets of findings. First, we consider the question of the appropriate specification for the aggregate production function for purposes of assessing whether capital–skill complementarity exists. We also discuss the appropriate definition of skilled labor. Given an answer to the specification question, we then report estimation results for the preferred specification using the various estimation techniques; without and with fixed effects removed (with FE) and using instrumental variable (IV) estimators. We then consider the robustness of our specification and estimation results using additional data on wage rates to augment our measures of skilled labor. Finally, we report the results of a Monte Carlo exercise which validates the reliability of the parameter estimates we report in the paper. We proceed by first reporting our estimation results obtained from using the unweighted–labor data and then commenting on the respective results obtained from using the weighted–labor data (the latter results are qualitatively similar to those obtained using the unweighted data and hence are presented in the appendix).

[10]Using the same educational attainment threshold across time and nations to classify the labor input by skill class can also be criticized. For example, workers who are just able to read and write might have been considered skilled workers at the beginning of the last century, whereas today, they might be classified as unskilled workers. Unfortunately, data that would allow us to adjust for quality does not exist.

5.1 Specification Search

The two competing specifications for testing the capital–skill complementarity hypothesis are given by our equations (1) and (2). Table 1 reports measures of fit for these two specifications for the two different estimation specifications: 1) the two–level CES model corrected for fixed effects (equations 6–7) and 2) the CES–nested–in–CD model corrected for fixed effects (equations 10–11), We regard these estimation specifications which correct for fixed effects as our baseline specifications; later in the paper we will consider alternative estimation models. According to the log–likelihood criterion, specification (1) is preferred to specification (2) in six out of eight specification searches using nonlinear estimation methods. It is worth mentioning that the various estimates we obtained for specification (2) were frequently implausible, in that many of the estimated distribution parameters and elasticity of substitution parameters took on implausibly negative values. This problem never arose in our various different regression results for the preferred specification (1) and therefore, in the remainder of the paper we focus on this specification (1) alone.

Table 1: Specification Search Results

Model Specification (Estimation Method)	Skilled Labor Definition	Specification 1 Log L	Specification 2 Log L
Two–Level CES (NLLS with FE)	Compl. Coll	237.1	237.1
	Att. Coll	236.0	235.5
	Compl. Sec.	232.8	237.7
	Att. Sec.	232.6	228.5
CES–in–CD (NLLS with FE)	Compl. Coll	243.7	221.0
	Att. Coll	230.8	220.2
	Compl. Sec.	241.9	229.2
	Att. Sec.	242.7	225.9

In addition to revealing which of the two competing CES production function specifications is preferred, the results presented in Table 1 also shed some light on the appropriate definition of skilled labor. If attention is restricted to the preferred specification (1) – column 3 of Table 1– we see that the log likelihood value is maximized for both the two–level CES and the CES–in–CD specifications when skilled labor is defined as those who have *completed college*. To our knowledge, these estimation findings using different definitions of skilled labor represent the first ever attempt to assess the appropriate definition of skilled labor; most researchers simply choose a threshold for skilled/unskilled labor without examining any alternative specifications. Our findings suggest that a popular choice for the skilled labor threshold as comprising those who have completed secondary education, may not be the choice most preferred by the data.[11]

5.2 Parameter Estimates

Tables 2–3 present coefficient estimates obtained from nonlinear regressions using the unweighted–labor data in various versions of specification (1).[12] In Table 2 we report parameter estimates for the two–level CES specifications (4) and (6). Under the column "NLLS," we report NLLS parameter estimates for specification (4) (the two–level model uncorrected for fixed effects) for each of the four ways of classifying skilled labor. Under the column "NLLS with FE," we report NLLS estimates for the log difference specification (6) (the two–level model corrected for fixed effects, FE) again for all four ways of classifying skilled labor. Finally, under the column "GMM–IV with FE" we report estimates from a GMM–IV procedure applied to the log–difference specification (6).[13]

The GMM–IV estimator was chosen to deal with a possible endogeneity problem, arising from the fact that the lagged error term $\epsilon_{i,t-1}$ in the log–difference specification (6) is likely to be correlated with time t values of the input variables, K_{it}, S_{it} and N_{it}. More generally, the perpetual inventory approach used to construct capital stock values (see the appendix for details) implies that K_{it} will always depend on such lagged error terms. To address these possible endogeneity problems, we employ the GMM–IV method and use as instruments lagged values of the right hand variables.[14] All of the NLLS estimation results reported in Tables 2 and 3 were obtained using economically plausible initial parameters. A grid search on the initial parameter values was also conducted to assess the robustness of the results.

Recall that in the two–level specification, capital–skill complementarity is said to obtain if $\rho > \theta$. Standard NLLS estimation of specification (4) without fixed effects or instruments yields estimates

[11]Papers where skilled labor is defined as those who have completed secondary education include Krusell et al. (2000) and Caselli and Coleman (2000) among others.

[12]Corresponding results using the weighted–labor data and specification (1) appear in Tables A3–A4 in the appendix.

[13]The GMM–IV procedure we use is different from the standard two–stage NLLS procedure in that it allows for the possibility of heteroscedastic and/or autocorrelated disturbances.

[14]In our GMM estimation of (6) and (10) (results from the latter are presented later in Table 3) we used $\log K_{i,t-1}$, $\log K_{i,t-2}$, $\log S_{i,t-1}$, $\log S_{i,t-2}$ and $\log N_{i,t-1}$, $\log N_{i,t-2}$ as instruments for the right hand side variables. We have used alternative sets of instruments including one set with $\log K_{i,t-1}$, $\log S_{i,t-1}$ and $\log N_{i,t-1}$ and another set with $\log K_{i,t-2}$, $\log S_{i,t-2}$ and $\log N_{i,t-2}$. We do not report these results as they are very similar to those reported in the paper.

for ρ and θ that imply capital–skill complementarity – see the "NLLS" column of Table 2. The difference $\rho - \theta$ is shown to be significantly positive only when skilled labor is defined as those who have attained or completed college.

However, estimates for our baseline specification, the nonlinear, two–level CES specification with fixed effects removed (6) as presented in the column "NLLS with FE", suggest that the evidence for capital–skill complementarity disappears once country specific fixed effects are taken into account. In particular, the estimated difference $\rho - \theta$ is found to be negative for three of the four skilled labor classifications, and is never significantly different from zero. Similarly, when we estimate the log difference specification (6) using the GMM–IV procedure that uses instruments for the right hand side variables and allows for both autocorrelation and heteroskedasticity in the error term, we continue to find a lack of evidence in favor of capital–skill complementarity; that is, we cannot reject the null hypothesis of no capital–skill complementarity – see the last column of Table 2. These findings of an absence of capital–skill complementarity are consistent with the work of Caselli and Coleman (2000) who obtain a similar result using a more indirect estimation method.

Table 3 reports a similar set of estimates for the nonlinear CES–nested–in–CD specification (10). Recall that for this specification, capital–skill complementarity obtains if the estimated value of $\theta < 0$; estimates of $0 < \theta \leq 1$ imply capital–skilled labor *substitutability* and capital–*unskilled* labor complementarity. As Table 3 reveals, for the nonlinear CES–nested–in–CD specification, we do observe estimates of θ that are positive and significantly different from zero, implying capital–*unskilled* labor complementarity. However, we note that the positive and highly significant NLLS estimates for θ are mainly observed in the models without fixed effects or instruments; in the fixed effects specification without or with instruments (NLLS with FE) and (GMM–IV with FE), the estimates of θ are positive and, with a single exception, are not significantly different from zero.

Table 2: Two–Level CES Nonlinear Estimation

Skilled Labor	Parameter	NLLS	NLLS with FE	GMM–IV with FE
	ρ	0.51934*** (0.06686)	0.22673*** (0.07779)	0.63517* (0.35936)
Completed	θ	0.26292** (0.13901)	0.49147 (18.54100)	0.73120 (598.76)
College	ρ - θ	0.25642* (0.16002)	-0.26474 (18.56400)	-0.09604 (598.58)
	$\log L$	-149.1	237.1	—
	ρ	0.54638*** (0.06839)	0.23861*** (0.07568)	0.78032 (1.0959)
Attained	θ	0.20459 (0.15939)	0.52216 (1.01680)	0.63377 (257.64)
College	ρ - θ	0.34179* (0.19206)	-0.28355 (1.04190)	0.14656 (256.94)
	$\log L$	-137.8	236.0	—
	ρ	0.54344*** (0.07226)	0.37839*** (0.07248)	0.78558 (0.70160)
Completed	θ	0.43718** (0.20005)	0.50824 (0.29852)	0.60498 (25.075)
Secondary	ρ - θ	0.10626 (0.20522)	-0.12985 (0.30483)	0.18059 (24.745)
	$\log L$	-129.0	232.8	—
	ρ	0.59841*** (0.08194)	0.50364*** (0.07467)	0.67895 (0.84761)
Attained	θ	0.45194*** (0.16511)	-0.07194 (0.20993)	0.33610 (4.1474)
Secondary	ρ - θ	0.14647 (0.19111)	0.57559 (0.20739)	0.34285 (3.7565)
	$\log L$	-138.5	232.6	—
Obs.		438	365	292

Notes: Standard errors are given in parentheses and were recovered using standard approximation methods for testing nonlinear functions of parameters. White's heteroskedasticity correction was used. *** Significantly different from 0 at the 1% level. ** Significantly different from 0 at the 5% level. * Significantly different from 0 at the 10% level.

Table 3: CES–Nested–in–CD Nonlinear Estimation

Skilled Labor	Parameter	NLLS	NLLS with FE	GMM–IV with FE
	θ	0.35175** (0.18157)	0.45712* (0.25482)	0.23068 (0.56734)
Completed	γ	0.60928*** (0.01352)	0.53608*** (0.10457)	0.36238*** (0.13471)
College	$\log L$	-185.1	243.7	—
	θ	0.53668*** (0.18897)	0.62413 (0.50871)	0.03111 (1.1565)
Attained	γ	0.64516*** (0.01179)	0.43305*** (0.03515)	0.20655 (0.24558)
College	$\log L$	-174.7	230.8	—
	θ	0.31833* (0.16877)	0.33990 (0.71577)	0.08753 (143.91)
Completed	γ	0.70372*** (0.01204)	0.63800 (0.90695)	0.47642 (0.51821)
Secondary	$\log L$	-165.2	241.9	—
	θ	0.36866*** (0.13689)	0.75042 (0.68256)	0.22003 (379.00)
Attained	γ	0.77621*** (0.01294)	0.45653*** (0.10581)	0.53275 (1.1929)
Secondary	$\log L$	-180.1	242.7	—
Obs.		438	365	292

Notes: Standard errors are given in parentheses and were recovered using standard approximation methods for testing nonlinear functions of parameters. White's heteroskedasticity correction was used. *** Significantly different from 0 at the 1% level. ** Significantly different from 0 at the 5% level. * Significantly different from 0 at the 10% level.

5.3 Discussion of the Estimation Results

To summarize, our main finding is that using a time–series, cross section panel of 73 countries, there appears to be little evidence to support the capital–skill complementarity hypothesis, especially once country specific fixed effects have been removed. Indeed, if attention is restricted to the log–difference estimation model then according to the NLLS and GMM results for both the two–level and CES–nested in–CD specifications, there is no evidence of any capital–skill complementarity for any definition of skilled labor. This finding is consistent with the possibility that over countries and across time, the extent of capital–skill complementarity (or substitutability) is subject to change, as argued by Goldin and Katz (1998).

According to the log–likelihood criterion, defining skilled labor as those persons who have completed or attained college is the preferred criterion in Table 1 for the baseline regression estimates based on the log–differenced version (fixed effects removed) of specification (1). We see from Tables 2 and 3, however, for the non–differenced model, the log–likelihood criterion favors a definition of skilled labor as those who have only completed a secondary education (see column 3 in Tables 2 and 3).

Finally, recall that the CES–nested–in–CD specification is just a restricted version of the two–level CES specification. In particular, the restriction is that in the latter, more general specification, ρ is equal to zero, so that the elasticity of substitution between capital and unskilled labor $\sigma_{K,N}$ and (symmetrically) between skilled and unskilled labor, $\sigma_{N,S}$ are both equal to unity. We can test this restriction by examining whether estimates of ρ as reported in Table 2 for the more general, two–level CES specification are significantly different from zero. If attention is restricted to the case where skilled labor is defined as those who have completed college, then this restriction is rejected for all three estimation methods, making the two–level CES specification the preferred specification. Our rejection of the restricted CES–nested–in–CD specification is consistent with the findings of Krusell et al. (2000) who obtained the same finding using only U.S. data.

5.4 Robustness of the Results using Adjusted Skilled Labor Data

We have also examined the robustness of our results by considering an alternative and possibly more appropriate definition for skilled/unskilled labor. As discussed earlier, this "weighted" labor dataset adjusts for disparities in efficiency units across workers who belong to different educational subgroups within the class of workers we have designated as skilled or unskilled labor. Adjusting the measures of skilled and unskilled labor for the returns earned by the various educational subgroups provides us with a more precise measure of the contribution of skilled labor to output. Further details concerning the construction of this weighted labor data can be found in the appendix.

Unfortunately due to a lack of data on returns to schooling for all 73 countries, this adjustment to the labor data eliminates approximately one–third of the countries our sample; we have 49 countries left, yielding just 294 observations (as compared with the 438 observations available in the full sample). Large sample sizes are particularly crucial to our work, as the results from estimating (the curvature of) the highly nonlinear nested CES production specifications requires a sufficiently large number of observations. Indeed, the GMM–IV estimation procedure for the nonlinear models, which requires the use of instruments, reduces the sample size even further to just 196 observations; the results from applying this procedure to the smaller weighted–labor dataset were unreliable resulting in economically implausible coefficient estimates and are not reported. The results from applying NLLS to the two–level model and the log–difference version of this model using the weighted–labor data (for which 294 observations were available) are presented in Tables A2–A4 in the appendix.

Table A2 (the analog of Table 1) shows that specification (1) remains the preferred specification for the two–level CES models for three out of four definitions of skilled labor. In contrast to our earlier findings using the unweighted skilled labor data, Table A2 reveals that for the CES–nested–in–CD specification, the weighted skilled labor data favors specification (2) for all four definitions of weighted–skilled–labor. We note however, that while the value of the log–likelihood function is higher for specification (2) the parameter estimates for this specification were frequently empirically implausible. In particular, the elasticity parameter θ was often greater than unity. This was never the case for specification (1), so we continue to focus attention on specification (1) only. Focusing on specification (1), Table A2 also reveals that defining skilled labor as workers who completed college is no longer the preferred definition when the weighted labor data are used. According to the log-likelihood values, the definition of skilled workers as those who completed secondary education is preferred in the two–level CES specification, and the definition of skilled workers as those who attained some college is preferred for the CES–nested–in–CD specification.

Table A3 (row1, column 1) reveals that for the un–differenced two–level CES model specification (1), the difference $\rho - \theta$ is significantly positive when skilled labor is defined as those who have completed college or those who have completed secondary education. However, correcting for fixed effects makes this estimate insignificant as was the case for the unweighted data. Indeed, we see that regardless of how skilled labor is defined, the difference $\rho - \theta$ is never significantly different from zero when the weighted labor data is used in the log–differenced version of the two–level CES specification (1) thus confirming our findings using the unweighted data. Table A4 reveals that for the specification (1) of the CES–nested–in–CD model there is again some weak evidence in favor of capital–skill *substitutability* (as opposed to capital–skill complementarity) in that estimates of θ are positive and sometimes significantly different from zero.

Finally, we note that in Table A3, the estimate of the parameter ρ is always positive and significantly different from zero for three of the four skilled labor definitions using the weighted data. Notice that using the weighted labor data, the log likelihood is maximized when skilled labor is defined as those who have completed secondary education. For this definition of skilled labor, we find that the estimate of ρ is significantly positive and that the null hypothesis of no capital skill complementarity cannot be rejected. This evidence again favors the more general, two–level CES specification over the more restricted CES–in–CD specification, with its assumption that $\rho = 0$. Despite some differences, these results are qualitatively similar in many respects to those obtained from the unweighted–labor dataset. In particular, two of our main findings, the absence of any evidence for capital–skill complementarity, and the rejection of the more restrictive CES–in–CD specification in favor of the general two–level specification, remain unchanged.

We have also tried to split the data to examine the sensitivity of our results to different subsamples of countries but to date, our estimates from such sample splits have been empirically implausible. We think this is due to having a limited number of observations that can not adequately capture variation in the curvature of our aggregate production functions.

5.5 Monte Carlo Experiments

Our main finding, that there appears to be little support for the capital–skill complementarity hypothesis at the level of aggregate production functions, rests on the parameter estimates we report in Tables 2–3 and A3–A4. A natural question concerns the reliability of the estimates we have obtained using nonlinear estimation techniques for either the two–level or CES–nested–in–CD specifications given our "small" samples. Indeed, Kumar and Gapinski (1974) and Thursby (1980) report results from Monte Carlo experiments examining the small sample properties of CES parameter estimates obtained using nonlinear and linear estimation procedures and find that all of the CES parameter estimates were reliable with the notable exception of the elasticity of substitution parameter estimate! Since this estimate is the primary concern of our study, we felt it necessary to undertake our own Monte Carlo experiments, which we describe below. We note that Kumar and Gapinski and Thursby examined only the standard CES specification, not the two–level specification that we examine, and they focused on linear and nonlinear estimation techniques that differ from those used in this study. Furthermore, they used far fewer observations than we have available in our panel dataset (e.g. Thursby used just 20 observations). For all of these reasons, a new set of Monte Carlo experiments seems warranted.[15]

The focus of our Monte Carlo experiments is on the small–sample properties of the NLLS estimators of the two–level CES parameters, ρ and θ. In principle, we could examine the economic characteristics of the elasticity of substitution estimators of all of the nested CES specifications suggested in the paper (using all the different combinations of aggregate production specifications and proxies for skilled labor). However, this would be an arduous task as nonlinear estimation of nested CES aggregate production specifications is particularly time–consuming. We have therefore chosen to examine the most unrestricted nested CES specification (the two–level CES specification) using as proxy for skilled labor, workers who have completed a post–secondary (college) education $S1$. We examine this specification using both the unweighted– and weighted–labor data.

In particular, we consider the stochastic counterparts of specification (1) given by

$$\log Y_{it} = \log A_{i0} + \lambda t + \frac{1}{\rho} \log \left[a[bK_{it}^{\theta} + (1-b)S1_{it}^{\theta}]^{\rho/\theta} + (1-a)N1_{it}^{\rho} \right] + \varepsilon_{it}, \tag{12}$$

and

$$\log\left(\frac{Y_{it}}{Y_{i,t-1}}\right) = \lambda + \frac{1}{\rho} \log \frac{\left[a[bK_{it}^{\theta} + (1-b)S1_{it}^{\theta}]^{\rho/\theta} + (1-a)N1_{it}^{\rho} \right]}{\left[a[bK_{i,t-1}^{\theta} + (1-b)S1_{i,t-1}^{\theta}]^{\rho/\theta} + (1-a)N1_{i,t-1}^{\rho} \right]} + u_{it}, \tag{13}$$

where ε_{it} and u_{it} are random disturbances with $\varepsilon_{it} \sim N(0, \sigma_{\varepsilon}^2)$ and $u_{it} \sim N(0, \sigma_u^2)$. The above stochastic production functions are used to generate data on output Y, employing our panel data of 73 (49) countries over six 5–year–interval periods for given values of capital K, unweighted (weighted) skilled labor with completed college $S1$, and unskilled labor, $N1$. We choose the elasticity of substitution parameters $\rho = 0.5$ and $\theta = 0.3$ to allow for capital–skill complementarity (i.e. $\rho - \theta = 0.2 > 0$). The other four parameters of the production functions were set as follows:

[15] To our knowledge, there is no prior work examining the small sample properties of estimates obtained from nonlinear or linear estimation of the two–level CES specification that we consider in this paper. Thus our Monte Carlo experiments are of independent interest beyond our application examining the capital–skill complementarity hypothesis.

Table 4: Estimates of Monte Carlo Experiments for the Two–Level CES

Model	Data	Parameter	Mean	Std. Dev.	Bias
Two–Level CES (NLLS no FE)(Eq.12)	Unweighted	ρ θ	0.51232 0.40507	0.13605 0.37007	0.01232 0.10507
Two–Level CES (NLLS with FE)(Eq.13)	Unweighted	ρ θ	0.50180 0.30102	0.02569 0.03450	0.00180 0.00102
Two–Level CES (NLLS no FE)(Eq.12)	Weighted	ρ θ	0.45938 0.40648	0.17686 0.39650	0.04062 0.10648
Two–Level CES (NLLS with FE)(Eq.13)	Weighted	ρ θ	0.48029 0.30858	0.05612 0.05621	0.01971 0.00858

$A_{i0} = 1$, $\lambda = 0.02$, $a = 0.4$, $b = 0.5$; these values fall in the range of coefficient estimates we obtained from our NLLS empirical exercises.

A critical consideration regarding the implementation of our simulation exercise is the choice of the variance for the random disturbances. Large values assigned to σ^2 would result in output series from specifications (12) and (13) that are almost purely stochastic. In contrast, very small values of σ^2 would result in output series that are completely deterministic. The variances σ_ε^2 and σ_u^2 were chosen according to the rule used in Kumar and Gapinski (1974) and Thursby (1980): the variances were chosen to yield certain R^2 values for the NLLS regressions. In particular, the expedient rule used to obtain the variances is

$$\begin{aligned} \sigma_\varepsilon^2 &= var(\log Y)(1 - R_\varepsilon^2), \\ \sigma_u^2 &= var[\log (Y_{t+1}/Y_t)](1 - R_u^2), \end{aligned}$$

where $R_\varepsilon^2 = 0.96$, and $R_u^2 = 0.30$. The values of R_ε^2 and R_u^2 were obtained from NLLS regressions. Thus we chose $\sigma_\varepsilon^2 = 0.11676$ and $\sigma_u^2 = 0.01548$ ($\sigma_\varepsilon^2 = 0.11640$ and $\sigma_u^2 = 0.01483$ for the weighted–labor data).

For each trial of the Monte Carlo experiment, 438 (365) observations on ε_{it} (u_{it}) were generated using a random number generator. A total of 100 sets of 438 (365) of ε_{it} (u_{it}) values were generated in this fashion.[16] Using these 100 disturbance sets we generated 100 sets of artificial output data (Y) using the actual data on capital, and skilled labor, and holding constant our parameter choices for the CES function, ρ, θ, A_0, λ, a, b. For the NLLS estimation employing these simulated data, the true parameter values were used as initial guesses in the hope that they will minimize the number of iterations required for convergence. Estimation of the models with fixed effects given by equation (13) always produced parameter values that are economically feasible. In contrast, estimation of the models without fixed effects given by equation (12) produced parameter values that are implausible (i.e. $\rho, \theta > 1$). For the estimates that have converged to implausible values, we have taken boundary values – ρ, $\theta = 0.96$ which implies $\sigma \approx 30$ – and re–estimate the other parameter conditional on these values.

Table 5 presents the sample mean, sample standard deviation and sample bias of the estimates of ρ and θ obtained using the stochastic specifications (12) and (13) and both the unweighted and weighted data. There are a number of points worth noting here. First, the sample means for the ρ and θ estimates in both models and datasets are relatively close to their actual values and the sample standard deviations and biases are rather small. Second, regardless of the dataset used, the estimates from the two–level CES specification obtained using NLLS and corrected for fixed effects have substantially lower sample standard deviation and bias than those from the specification that is not corrected for fixed effects. In particular, when we use the unweighted dataset, the sample standard deviation in the estimates of ρ is 0.02569 in specification (13) as compared to 0.13605 in (12) and the sample standard deviation in the estimates of θ is 0.03450 in (12) as compared to 0.37007 in (13), which is more than ten times smaller. Third, ρ and θ estimates are in general more biased when we use the weighted–labor data. This is expected since our sample reduces substantially from 438 (365) to 294 (245) observations. Overall, these results suggest that NLLS estimation of the two–level CES specification provides accurate estimates of the elasticity of substitution parameters, ρ and θ, and therefore can be used successfully in testing the capital–skill complementarity hypothesis.[17]

[16] For the weighted–labor data 100 sets of 294 (245) of ε_{it} (u_{it}) values were generated.

[17] Histograms for the parameters ρ and θ obtained from the Monte Carlo experiments show densities that in general do not deviate from the normal distribution. More formally, the Jarque–Bera test of normality shows that in six out of eight distributions (four models, each with two elasticity parameters ρ and θ) normality can not be rejected. The two distributions for which we reject normality are those of the parameter θ for the two–level CES (NLLS no FE) using both the weighted and unweighted data. One explanation is that some of the θ estimates in these models

6 Conclusions

The aim of this paper is to examine the cross–country evidence for capital–skilled labor complementarity using aggregate production function specifications and a time–series, cross–section panel of countries. In particular, we address three empirical questions. First, what is the best specification of the aggregate production technology for purposes of examining the capital–skill complementarity hypothesis? Second, how is skilled labor measured? We consider four different possible classifications an examine which definition the data prefer. Finally, is there any cross–country evidence in support of the capital–skill complementarity hypothesis? With regard to the first issue we find that specification (1) is the preferred specification, and that the restricted, CES–nested–in–CD specification, appears to be less supported by the data than the two–level CES form. Second, we find that by the log–likelihood criterion, the preferred definition of skilled labor consists of those who have completed college, a higher threshold for defining skilled labor than is typically used in the literature. However, this finding does not hold up when the labor data are weighted using returns to schooling. Finally, and perhaps most importantly, we do not find significant differences in the elasticity parameters that would allow us to reject the null hypothesis of no capital–skill complementarity. A Monte Carlo exercise provides us with some confidence in the regression results that support this main finding.

We conclude that, at the aggregate production function level, there is little evidence to support the capital–skill complementarity hypothesis and therefore no justification for modifying the standard neoclassical aggregate production technology to account for this hypothesis in macro–growth modeling. While it may be the case that capital–skill complementarities exist at a more disaggregate level, for instance at the manufacturing level, or at the level of individual countries, at the aggregate level of production function analysis and across countries, these complementarities seem to disappear. An intriguing explanation for this finding is that the extent of capital–skill complementarity (or substitutability) varies with a country's stage of development and is therefore subject to change over time, as Goldin and Katz (1998) have convincingly argued. If this hypothesis is true, then, consistent with our findings, evidence in support of the capital–skill complementarity hypothesis should be especially difficult to obtain using a time–series, cross section panel of countries.

have converged to implausible values and, as mentioned above, these estimates were replaced by the boundary value $\theta = 0.96$.

Appendix

The Data

The data used in this paper (unweighted and weighted) are available from the authors upon request.

- *Income (Y)* [Source: PWT–5.6]

Cross–country real GDP per worker and real GDP per capita are in constant dollars (1985 international prices) using the Chain index as described by Summers and Heston (1991). These data are from the Penn World Tables (PWT), Version 5.6 and are available on–line at:
http://datacentre.chass.utoronto.ca/pwt/index.html.

- *Physical capital stocks (K)* [Source: PWT–5.6]

Physical capital is constructed using the perpetual inventory approach with investment shares data obtained from PWT–5.6. In particular, the physical capital stock is calculated by summing investment from its earliest available year (1960 or earlier) to 1990 with the annual depreciation rate fixed at 6 percent. The initial physical capital stock is determined by the initial investment rate, divided by the depreciation rate plus the growth rate of investment during the subsequent ten years. See Duffy and Papageorgiou (2000) for further details concerning this procedure.

- *Skilled and Unskilled Labor (S, N)* [Source: Barro and Lee (2000), and Lee (2001)]

We construct four alternative proxies for skilled and unskilled labor as the definition of skilled/unskilled labor is arbitrary. These proxies are constructed using enrollment rates data from Barro and Lee (2000) and multiplying these rates by the sized of the total labor force. Our four proxies for skilled and unskilled labor are as follows:

Unweighted data

1. $S1$ is equal to the number of workers that have completed post–secondary education and $N1$ is equal to the rest of the workers in the labor force.

2. $S2$ is equal to the number of workers that have attained at least some post–secondary education and, $N2$ is equal to the rest of the workers in the labor force.

3. $S3$ is equal to the number of workers that have completed secondary education, and $N3$ is equal to the rest of the workers in the labor force.

4. $S4$ is equal to the number of workers that have attained at least some secondary education, and $N4$ is equal to the rest of the workers in the labor force.

Weighted data

Within a given skill class say, Si or Ni, $i = 1,2,3$ or 4 we weigh individuals by the length in years of their schooling level times the return to schooling. In addition, the aggregate is constructed so that it is measured in terms of the efficiency units of the lowest educational subcategory included in the skill class. Lengths of educational attainments subgroups by country are from Lee (2001). Returns to schooling by nation are taken from Bils and Klenow (2000), and were obtained following the Mincerian approach which assumes that log–wages are linear in years of schooling.

An example: Let $l_{i,j}$ be the length in years of educational level j in country i, $L_{i,j}$ the number of workers with this schooling level, and ϕ_i is the Mincerian return in country i. For nation i, $S3$ and $N3$ are computed as follows:

$$\begin{aligned} S3(i) &= L_{i,cs} + \phi_i\, l_{i,sps}\, L_{i,sps} + \phi_i\, l_{i,cps} L_{i,cps}, \\ N3(i) &= L_{i,cp} + \phi_i\, l_{i,ss}\, L_{i,ss}, \end{aligned}$$

where cp, ss, cs, sps and cps denote completed primary, some secondary, completed secondary, some post–secondary and completed post–secondary education, respectively.
The Barro and Lee (2000) data set is available on–line at: http://www2.cid.harvard.edu/ciddata

- *Labor Force* [Source: PWT–5.6]

The cross–country data set on the labor force is calculated from the PWT–5.6 series on GDP per capita and GDP per worker. It represents the population between the ages of 15 and 65 (taken to represent the labor force).

Table A1: Mean Values of Unweighted–Data from the 73 Country Sample

Country	Code	GDP (mill. US$)	Capital (mill. US$)	Skilled Lab. ($S1$) (thous.)	Unskilled Lab. ($N1$) (thous.)
Algeria	DZA	44620.1	97958.8	3951.9	24.6
Argentina	ARG	150309.3	285059.0	9764.3	291.2
Australia	AUS	173178.0	522017.9	608.1	5804.0
Austria	AUT	71539.6	188862.3	38.9	3329.8
Bangladesh	BGD	98086.8	42154.0	124.9	24255.5
Brazil	BRA	406421.4	733594.1	756.8	40055.5
Belgium	BEL	98489.2	259548.9	217.5	3642.6
Bolivia	BOL	9241.7	17061.4	43.8	1660.3
Canada	CAN	308801.9	758688.9	739.6	9960.6
Chile	CHL	39315.5	85170.8	116.9	3550.6
Colombia	COL	68509.0	108933.2	143.8	7764.8
Costa Rica	CRI	7094.8	6146.6	25.2	702.4
Cyprus	CYP	3233.0	8625.1	13.8	268.8
Denmark	DEN	55921.8	160162.7	182.3	2404.7
Ecuador	ECU	20081.0	41964.5	62.7	2302.4
El Salvador	SLV	7877.6	3517.4	16.5	1366.9
Finland	FIN	48897.2	172168.6	87.8	2256.6
France	FRA	576919.9	1625109.1	494.5	22808.5
Germany	DEU	677584.3	1444383.0	482.3	27216.6
Ghana	GHA	9813.9	7368.2	14.4	4350.2
Greece	GRC	49610.5	118409.6	164.3	3439.2
Guatemala	GTM	14366.8	14185.8	14.6	1920.2
Haiti	HTI	4739.6	2802.3	6.1	2383.0
Honduras	HND	4736.3	6786.2	8.1	1051.3
Iceland	ICE	2245.1	6219.7	3.3	105.4
India	IND	631421.3	828804.9	2118.5	257681.1
Indonesia	IDN	180966.6	259253.0	59.5	53720.7
Iran	IRN	153674.3	226936.6	95.7	10894.0
Iraq	IRQ	62576.6	79507.4	48.6	3250.8
Ireland	IRL	21031.5	54008.1	39.9	1190.0
Israel	ISR	27462.0	63439.3	95.1	1267.3
Italy	ITA	513760.7	1453670.2	273.1	21598.0
Jamaica	JAM	5086.1	14084.8	5.5	889.7
Japan	JPN	1085463.9	3199481.3	4497.3	65976.1
Jordan	JOR	6094.8	7796.0	11.6	547.8
Kenya	KEN	12896.4	22662.3	18.5	6991.0

Note: The sources for these data are PWT–5.6 and Barro and Lee (2000). Country specific mean values presented above have been rounded to the first decimal place.

Table A1: Mean Values of Unweighted–Data from the 73 Country Sample, continued.

Country	Code	GDP (mill. US$)	Capital (mill. US$)	Skilled Lab. ($S1$) (thous.)	Unskilled Lab. ($N1$) (thous.)
Korea, Rep.	KOR	123619.8	173122.2	651.0	13278.1
Malawi	MWI	2970.0	2888.4	3.7	2685.4
Malaysia	MYS	46709.4	88587.3	4973.3	4973.3
Mali	MLI	3156.0	1892.7	3.6	2322.5
Mauritius	MUS	3660.0	3999.2	3.0	485.5
Mexico	MEX	325533.8	499518.5	409.2	19571.4
Mozambique	MOZ	11780.6	2778.0	0.0	6403.1
Myanmar (Burma)	MMR	16679.8	14309.7	58.3	14419.5
Netherlands	NLD	145453.1	384517.7	210.9	5087.6
New Zealand	NZL	31867.4	57557.5	96.5	1174.9
Norway	NOR	44634.4	147087.0	61.2	1783.6
Pakistan	PAK	90718.0	79640.2	302.0	23272.3
Panama	PAN	5486.0	10919.8	24.7	614.8
Paraguay	PRY	5844.9	7146.3	19.2	982.6
Peru	PER	43241.4	85691.6	209.3	4845.3
Philippines	PHI	74413.5	115076.7	1166.9	15781.4
Portugal	PRT	44167.8	94405.4	44.3	3982.1
Senegal	SEN	6137.7	4270.0	14.3	2486.4
Sierra Leone	SLE	3471.8	315.328.1	3.8	1235.9
Singapore	SGP	14973.3	36424.8	13.4	943.4
Spain	ESP	257028.1	637275.6	250.8	12570.6
Sri Lanka	LKA	23021.0	12767.7	22.0	5065.6
Sudan	SDN	14658.3	20107.2	13.6	5998.2
Sweden	SWE	99908.5	261627.0	242.2	3760.3
Switzerland	CHE	87821.5	275816.1	162.7	2915.5
Tanzania	TZA	8161.8	8599.8	72.3	8666.3
Thailand	THA	98267.9	137663.4	424.3	21865.2
Tunisia	TUN	14045.3	17003.8	17.9	1810.7
Turkey	TUR	123388.5	238604.3	182.9	18819.1
Uganda	UGA	6959.6	2171.8	5.6	5701.7
United Kingdom	GRB	563966.7	1132350.1	1103.4	25574.0
United States	USA	3307524.9	8438179.1	13905.4	88791.9
Uruguay	URY	12456.0	23513.3	40.1	1094.7
Venezuela	VEN	95991.3	205740.7	114.1	4396.6
Zaire	ZAR	13408.9	6921.8	20.6	10594.6
Zambia	ZMB	5199.2	21789.5	4.5	1875.8
Zimbabwe	ZWE	8043.5	18997.5	20.0	2871.7

Note: The sources for these data are PWT–5.6 and Barro and Lee (2000). Country specific mean values presented above have been rounded to the first decimal place.

Estimation Results with Weighted–Labor Data

Table A2: Specification Search (weighted–labor data)

Model Specification (Estimation Method)	Skilled Labor Definition	Specification 1 Log L	Specification 2 Log L
Two–Level CES (NLLS with FE)	Compl. Coll	193.3	192.5
	Att. Coll	194.3	194.3
	Compl. Sec.	195.9	194.9
	Att. Sec.	193.7	195.4
CES–in–CD (NLLS with FE)	Compl. Coll	183.2	190.8
	Att. Coll	185.7	192.6
	Compl. Sec.	180.3	191.4
	Att. Sec.	170.4	190.2

Table A3: Two–Level CES Nonlinear Estimation (weighted–labor data)

Skilled Labor	Parameter	NLLS	NLLS with FE
	ρ	0.58146*** (0.11091)	0.40482 (0.61130)
Completed	θ	0.08585 (0.08352)	0.35461*** (0.10306)
College	ρ - θ	0.49561*** (0.16003)	0.50211 (0.60796)
	$\log L$	-57.3	193.3
	ρ	0.47987*** (0.11082)	0.36999*** (0.09621)
Attained	θ	0.47505 (0.33170)	-0.55621 (1.46714)
College	ρ - θ	0.00481 (0.35710)	0.92621 (1.46458)
	$\log L$	-50.9	194.3
	ρ	0.26689*** (10102)	0.45315*** (0.09682)
Completed	θ	1.13733*** (0.31369)	0.84715** (0.41589)
Secondary	ρ - θ	-0.87045*** (0.33146)	-0.39400 (0.43291)
	$\log L$	-24.5	195.9
	ρ	0.36132*** (0.09018)	0.49659*** (0.09164)
Attained	θ	0.35623** (0.18284)	0.56249** (0.24232)
Secondary	ρ - θ	0.00509 (0.21229)	0.06590 (0.24745)
	$\log L$	-30.8	193.7
Obs.		294	245

Notes: Standard errors are given in parentheses and were recovered using standard approximation methods for testing nonlinear functions of parameters. White's heteroskedasticity correction was used. *** Significantly different from 0 at the 1% level. ** Significantly different from 0 at the 5% level. * Significantly different from 0 at the 10% level.

Table A4: CES–Nested–in–CD Nonlinear Estimation (weighted–labor data)

Skilled Labor	Parameter	NLLS	NLLS with FE
	θ	0.46825 (0.30181)	0.20057 (0.57872)
Completed	γ	0.68693*** (0.17502)	0.39971*** (0.03699)
College	$\log L$	−71.6	183.2
	θ	0.45075 (0.28610)	0.58865 (1.33690)
Attained	γ	0.72299*** (0.01680)	0.43746*** (0.03825)
College	$\log L$	−60.6	185.7
	θ	1.10118*** (0.28571)	0.94627*** (0.35455)
Completed	γ	0.78039*** (0.01530)	0.59882*** (0.03739)
Secondary	$\log L$	−28.3	180.3
	θ	1.11141*** (0.26531)	0.53203** (0.22830)
Attained	γ	0.82371*** (0.01530)	0.71193*** (0.03336)
Secondary	$\log L$	−30.9	170.4
Obs.		294	245

Notes: Standard errors are given in parentheses and were recovered using standard approximation methods for testing nonlinear functions of parameters. White's heteroskedasticity correction was used. *** Significantly different from 0 at the 1% level. ** Significantly different from 0 at the 5% level. * Significantly different from 0 at the 10% level.

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