Nonlinearities in Capital-Skill Complementarity

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Abstract

This paper uses a novel dataset to test the capital-skill complementarity hypothesis in a cross-section of countries. It is shown that for the full sample there exists evidence in favor of the hypothesis. When we arbitrarily split the full sample into OECD and non-OECD countries, we find no evidence in favor of the hypothesis for the OECD subsample, but strong evidence for the non-OECD subsample. When we use Hansen's (2000) endogenous threshold methodology we find that initial literacy rates and initial per capita output are threshold variables that can cluster countries into three distinct regimes that obey different statistical models. In particular, the regime with moderate initial per capita income but low initial education exhibits substantially higher capital-skill complementarity than the regime with low income and low education and the regime with high education. This cross-country nonlinearity in capital-skill complementarity is consistent with the time-series nonlinearity found by Goldin and Katz (1998) using U.S. manufacturing data, and promotes the view that the phenomenon maybe a transitory one.

Keywords: Capital-skill complementarity, nonlinearities, parameter heterogeneity, regimes.

JEL classification: O40, O47.

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1 Introduction

This paper reports new findings on Griliches' (1969) hypothesis of capital-skill complementarity. The hypothesis states that capital is more complementary with skilled than unskilled labor. Griliches' hypothesis has received renewed attention in the macroeconomics literature as researchers are determined to move away from the straight-jacket Cobb-Douglas specification. Evidence in favor of the hypothesis would have important implications both in guidance on how to specify the aggregate production function in theoretical work, but also in reassessing the robustness of existing empirical findings. The hypothesis is especially relevant to the growth literature as it pertains to the controversy about the two competing determinants of economic growth, namely input accumulation and technical progress. In particular, evidence in favor of the capital-skill complementarity hypothesis would elevate the relative importance of input accumulation (such as physical and human capital) in promoting growth.

The earliest use of capital-skill complementarity in the macroeconomics-growth literature is Galor and Weil (1996).[1] More recently there is an emerging literature that is interested in the empirical/quantitative implications of the hypothesis; see, e.g. Flug and Hercowitz (2000), Krusell, Ohanian, Rios-Rull and Violante (2000), Caselli and Coleman (2002, 2004), Ruiz-Arranz (2002), Caselli and Wilson (2004), Duffy, Papageorgiou and Perez-Sebastian (2004) and Lindquist (2004). There is also an emerging theoretical literature in which the main force of the development process stems from the assumption of capital-skill complementarity; see, e.g. Stockey (1996), Galor and Moav (2000, 2002, forthcoming) and Galor and Weil (2000).[2]

In this paper, we use a new cross-country dataset (constructed by Caselli and Coleman (2004)) to test the hypothesis. The novelty of this dataset is that it contains observations on wages of skilled and unskilled labor across a wide range of developed and developing countries. Cross-country data on wages of skilled/unskilled labor are scarce and present us with a unique opportunity to test the hypothesis using simple linear econometric estimation techniques. This is important as recent papers use highly nonlinear nested Constant-Elasticity-of-Substitution (CES) aggregate

[1]These authors argued that due to this complementarity, the relative wages of women will increase in the process of development, and would permit a reduction in fertility along with an increase in female labor force participation. Their underlying assumption is that women have relatively lower innate endowment of physical labor and thus relatively more endowment of mental (skilled) labor.

[2]In addition, the hypothesis has been extensively tested by many microeconomic studies that used firm and industry-level data. For a representative sample of such studies see Hamermesh (1993).

production functions which are shown to be quite difficult to accurately estimate. Even though our examination of the capital-skill complementarity hypothesis is limited to a single year and a sample of 46 countries, we show that significant progress can be made in understanding the hypothesis' role and potential implications.

The main findings of the paper are as follows: First we find that for our full sample of 46 countries there exists evidence in favor of the capital-skill complementarity hypothesis. Second, when we arbitrarily split our sample into OECD and non-OECD subsamples, we find no evidence in favor of the hypothesis for the OECD subsample but strong evidence for the non-OECD subsample. Third, after employing the data-sorting method developed by Hansen (2000), that allows the data to endogenously select regimes, we find that initial literacy rates and initial per capita output are threshold variables that can cluster countries into three distinct regimes that obey different statistical models. Our last finding reveals that countries with low initial literacy rates (below 68%) but respectable initial per capita output (above \$2042), exhibit capital-skill complementarity that is substantially more pronounced than in countries with low literacy (below 68%) and low income (below \$2042), and in countries with high literacy (above 68%). This cross-country nonlinearity in capital-skill complementarity is qualitatively consistent with the time-series nonlinearity found by Goldin and Katz (1998) using U.S. manufacturing data. Both results point to the intriguing possibility that capital-skill complementarity is a transitory phenomenon.

The rest of the paper is organized as follows. Section 2 summarizes alternative approaches in testing the capital-skill complementarity hypothesis and discusses the specific approach used in this paper. Section 3 discusses the data, estimation method and results, paying particular attention to the potential existence of multiple regimes with different levels of capita-skill complementarity. Section 4 examines the robustness of our baseline results to alternative specifications and threshold models. Section 5 discusses the implications of our findings to the existing literature. Section 6 concludes.

2 Testing the Capital-Skill Complementarity Hypothesis

There are at least three ways by which the capital-skill complementarity hypothesis can be empirically tested. First, the hypothesis can be tested using the aggregate production function directly. Second, it can be tested using a two-step conditional approach. Finally, it can be tested using a quasi-fixed cost function approach. We briefly discuss these approaches next.

2.1 The nested-CES production function approach

A functional form that is general enough to accommodate different elasticities of substitution is the two-level CES production specification that was pioneered by Sato (1967). A special case of this functional form is given by

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

where Y is aggregate output, K is capital stock, S is skilled labor, N is unskilled labor, A is a positive technological parameter, a, b are distribution parameters and θ, $\rho \leq 1$ are the elasticity of substitution parameters ($\theta = \rho = 0$ imply the Cobb-Douglas specification).

Equation (1) implies that the capital-skill complementarity hypothesis holds iff $\rho > \theta$.[3] This approach, which requires estimation of ρ and θ directly from the two-level CES function given by equation (1), involves using nonlinear estimation techniques.[4] As demonstrated by Duffy, Papageorgiou and Perez-Sebastian (2004), notwithstanding substantial improvements in nonlinear estimation, obtaining reliable estimates of the relative size of elasticity parameters (ρ and θ) proves to be quite cumbersome and problematic. This is primarily because the relevant elasticity parameters depend crucially on the curvature (not the slope) of the production function thus making them second order parameters and difficult to accurately estimate.

2.2 The two-step conditional approach

The second approach, employed by Fallon and Layard (1975), is to use the production function in equation (1) along with competitive market conditions to obtain the following two equations:

$$\ln(r/w_1) = \ln[b/(1-b)] + (\theta - 1)\ln(K/S) \tag{2}$$

[3] For general production technologies with more than two inputs there is no single definition for the elasticity of substitution between pairs of inputs. The two most commonly used definitions are the *Allen-Partial Elasticity of Substitution* (APES) and *Direct Elasticity of Substitution* (DES). APES measures the percentage change in the ratio of two inputs in response to a change in the ratio of the two input prices, holding all other prices and output quantity constant. DES measures the percentage change in the ratio of two inputs in response to a change in the ratio of the two input prices, holding all other prices, inputs and output quantity constant. Duffy, Papageorgiou and Perez-Sebastian (2004, pp. 329-330) have shown that in the two-level CES specification (1) the capital-skill complementarity hypothesis holds iff $\rho > \theta$ regardless of which elasticity measure is used.

[4] Alternatively, estimation of a more disaggregated production function is possible, e.g. through the use of a translog specification (see, e.g. Bergström and Panas (1992), and Ruiz-Arranz (2002)). However, much of the focus has been placed on the two-level CES specifications used extensively in recent papers that attempt to examine the implications of the capital-skill complementarity hypothesis.

$$\ln(q/w_2) = \ln[a/(1-a)] + (\rho - 1)\ln\left[b\,(K/N)^{\theta} + (1-b)\,(S/N)^{\theta}\right]^{1/\theta}, \tag{3}$$

where a, b, θ, ρ are as defined previously, r is rental income, q is the price of the product $[bK^{\theta} + (1-b)S^{\theta}]^{1/\theta}$, and w_1 and w_2 are average wages of skilled and unskilled labor, respectively. Obviously, equations (2-3) ought to be estimated sequentially, since equation (2) provides an estimated coefficient for θ needed to construct the variables q and $\left[b\,(K/N)^{\theta} + (1-b)\,(S/N)^{\theta}\right]^{1/\theta}$ in equation (3).[5] Once again the capital-skill complementarity hypothesis holds iff $\rho > \theta$. The basic difficulty in testing the hypothesis using this approach is the lack of reliable international data on interest rates. In addition, employing a two-stage conditional estimation procedure may result in biased estimates.

2.3 The quasi-fixed cost function approach

A third approach based on Brown and Christensen (1981) derives a skilled-labor share equation of a quasi-fixed cost function that has a translog form. After cost minimization under constant returns to scale, the following "share equation" is obtained:

$$S_1 = \alpha_1 + \gamma_{11}\ln(w_1/w_2) + \gamma_{1K}\ln(K/Y), \tag{4}$$

where S_1 is the skilled-labor share of the total wage bill, w_1/w_2 is skilled to unskilled labor wage premium, and K/Y is the capital-output ratio. A positive coefficient for γ_{1K} in equation (4) implies capital-skill complementarity. This is because when capital and skilled labor are complements, an increase in capital intensity (K/Y) causes an increase in the skilled-labor share of the total wage bill (S_1). Similarly, a positive coefficient for γ_{11} implies skilled-unskilled labor complementarity. The logic is the same as above. An increase in the skilled-unskilled labor wage premium (w_1/w_2) causes an increase in the skilled-labor share of the total wage bill. Finally, α_1 can be interpreted as the average of the skilled-labor share. Derivation of equation (4) appears in the appendix.

In this paper, we will be testing the capital-skill complementarity hypothesis by using equation (4) as our baseline estimation equation. Even though, there are quite a few studies that use industry-level data in equation (4) to test the capital-skill complementarity hypothesis (see, e.g. Berman, Bound and Griliches (1994), Berman, Bound and Machin (1998), and Goldin and Katz (1998)), to our knowledge, this is the first paper that uses aggregate cross-country data.

[5] For more discussion on this approach see Fallon and Layard (1975, pp. 285-286).

An advantage of using equation (4) is that we can sidestep the cumbersome nonlinear estimation (and the problems associated with it) required by equation (1) and use standard linear econometric estimation techniques in testing the hypothesis. More importantly, equation (4) allows us to examine the sensitivity of the baseline results from the full sample to alternative subsamples. This is essential to this paper, as we want to search for potential nonlinearities in capital-skill complementarity across the development process. It is worth noting that testing the hypothesis for subsamples of countries by using equation (1) is not possible given the current availability of data, as the significant reduction in sample size does not permit for the accurate estimation of the curvature of the production function.

3 Data, Estimation and Results

Our estimation of equation (4) involves cross-sectional data on 52 countries. We consider both linear least squares regressions as well as threshold estimation techniques to obtain parameter estimates. We begin by briefly describing the data used in our estimation.

3.1 The data

We use a novel cross-country dataset constructed by Caselli and Colleman (2003) to estimate the "share equation" (4). The novelty of our dataset lies on availability of observations on wages of skilled and unskilled labor across a wide range of developed and developing countries. In addition, the dataset includes observations on skilled-labor shares and capital-output ratio. The downside is that our examination of the capital-skill complementarity hypothesis is limited to a single year for a sample of 46 countries which cross-country wage data are available.

More specifically, data for skilled-labor share (S_1), skilled to unskilled wage premium (w_1/w_2), capital stock (K) and output (Y) are from Caselli and Coleman (2003) who in turn obtained these data from the following sources:[6]

- Data for K and Y are from Hall and Jones (1999). Y is GDP per worker in international dollars and K is the stock of capital per worker estimated using the perpetual inventory method. The data for K and Y are for 1988.

[6]For more discussion on these data and their sources see Caselli and Colleman (2004, pp. 6-9, 30–31).

- Data for w_1/w_2 are from Bills and Klenow (2000) and Caselli and Coleman's calculations. Caselli and Coleman (2003) estimate w_1^i/w_2^i as $\exp(\beta^i n)$, where β^i is the Mincerian return in country i, and n is the difference in schooling years between skilled labor (L_1^i) and unskilled labor (L_2^i). The cross-country Mincerian returns data are from Bills and Klenow (2000) (who in turn obtained the data from Psacharopoulos (1994)) and differences in schooling years data are from Lee (2001).

- Data for S_1 are constructed from the Barro and Lee (1993) dataset, and authors' calculations. By definition $S_1 = \frac{w_1 L_1}{w_1 L_1 + w_2 L_2}$. However, since data on wages are available only as the ratio of skilled to unskilled labor (w_1/w_2), we make a simple transformation to rewrite $S_1 = \frac{(w_1/w_2)L_1}{(w_1/w_2)L_1 + L_2}$. L_2 (unskilled labor) is constructed as an aggregate of workers with no education and with some primary education, whereas L_1 (skilled labor) is an aggregate of the remaining labor. The data for $L_1$and L_2 are from Barro and Lee (1993) for the year 1985.

For our threshold estimation exercises we use data on initial (1960) output per worker (from Penn World Tables 5.6), and initial (1960) adult literacy rates defined as the fraction of population over the age of 15 that is able to read and write (from the World Bank's *World Report*). Due to data constraints with initial literacy rates our sample is reduced from 52 countries (the original Caselli-Coleman sample) to 46 countries.[7] We note that in all but the threshold estimation regressions which require data on initial literacy rates, we perform robustness tests of our results to the 52-country sample. All of the data used in this paper appear in Table A1 in the appendix.

3.2 Estimation

We obtain parameter estimates for four different models based on equation (4) using ordinary least squares (OLS). Given the small number of observations in our full sample and the subsamples considered, we have implemented the bootstrap which performs inference that is more reliable in finite samples than inferences based on conventional asymptotic theory.[8]

In our baseline model (Model 1), we estimate equation (4) in which the regressors are logs of the skilled to unskilled labor wage ratio (w_1/w_2), and the capital-output ratio (K/Y) . With the relevant coefficient for capital-skill complementarity (γ_{1K}) in mind, we also examine the robustness

[7]The countries excluded from the Caselli-Coleman sample are Botswana, China, Cyprus, Hungary, Poland, Taiwan.

[8]In particular, samples are randomly drawn (with replacement) from the OLS residuals and the fitted values are used to estimate the coefficients as means of 1000 replications of the procedure.

of the results from our baseline model by estimating three modifications of equation (4): Following Goldin and Katz (1998 pp. 720-722) we consider an estimation equation that drops w_1/w_2 (Model 2) and another that drops w_1/w_2 and adds an output (Y) variable (Model 3). Finally, we estimate an equation that includes all variables, w_1/w_2, K/Y and Y (Model 4). The reason for eliminating w_1/w_2 in Model 2 is that cross-sectional wage variation could largely reflect skill differences and not exogenous wage variations. Also, the estimates could suffer from a division bias since w_2 appears in the denominators of both the dependent variable and the wage premium variable. The reason for adding Y in Modes 3 and 4 is to account for cyclical differences in the extend to which skilled and unskilled labor are quasi-fixed factors. Also, the addition of Y allows for the possibility that the production function is non-homothetic.

Recent papers by Durlauf and Johnson (1995), Brock and Durlauf (2000), Durlauf, Kourtellos and Minkin (2001), and Masanjala and Papageorgiou (2004), argue that the assumption of a single linear model representing all countries is inappropriate. Put differently, parameter homogeneity, which implies that model parameters are country-invariant, is implausible in light of the vast heterogeneity that exists among countries. Following this literature, in addition to obtaining parameter estimates in the entire sample and arbitrarily chosen subsamples (i.e. OECD and non-OECD), we also employ Hansen's (2000) data-splitting methodology to examine the possibility of parameter heterogeneity and nonlinearities in our capital-skill complementarity equation (4).

3.3 Estimation results from the entire sample

We start by testing the capital-skill complementarity hypothesis using our full sample of 46 countries. Results from all four models are presented in Table 1. In our baseline Model 1 (column 2), the relevant coefficient estimate of γ_{1K} is 0.34620 and statistically significant at the 1% level. This is evidence in favor of capital-skill complementarity in the full sample. Columns 3-5 in Table 1, show that our baseline model result is robust to the alternative Models 2-4. In particular, coefficient estimates of γ_{1K} are 0.34780 in Model 2, 0.19286 in Model 3 and 0.15743 in Model 4, and are significantly different from zero at the 1% level, 1% level, and 5% level, respectively.

It is also interesting to notice that the coefficient estimate for Y is positive and statistically significant in both Models 3 and 4 which may suggest that the production function is non-homothetic. As expected inclusion of Y in Models 3 and 4 reduces the magnitude of γ_{1K} but does not change our key result of capital-skill complementarity. The estimates of γ_{11} in Model 1 is negative and in

Table 1: Cross-country regressions for full sample

Specification	Model 1	Model 2	Model 3	Model 4
Constant	0.44598***	0.42889***	−0.43172*	−0.73992**
	(0.05823)	(0.03755)	(0.24314)	(0.30178)
$\ln(w_1/w_2)$	−0.04024			0.17359
	(0.10331)			(0.10412)
$\ln(K/Y)$	0.34620***	0.34780***	0.19286***	0.15743**
	(0.05055)	(0.04979)	(0.06223)	(0.06438)
$\ln Y$			0.10384***	0.13215***
			(0.02907)	(0.03317)
s.e.e.	0.68344	0.68406	0.53294	0.49885
Adj. R^2	0.51	0.51	0.62	0.63
Obs.	46	46	46	46

Notes: The dependent variable is skilled-labor share of the wage bill (S_1). w_1/w_2 is skilled-unskilled wage premium, K/Y is capital-output ratio and Y is output. Robust standard errors are given in parentheses. 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.

Model 4 positive, but neither is significantly different from zero. It is for this reason that estimates of γ_{1K} in Models 1 and 2, and Models 3 and 4 are quite similar. Even though, the Adj. R^2 statistic is relatively high in all four models it is highest in Models 3 and 4 (0.62 and 0.63, respectively), which could suggest that modifications of Models 1 and 2 to incorporate an output variable were reasonable.

To summarize, the main finding here is that the baseline model and all three alternative models obtain a positive and statistically significant coefficient estimate of γ_{1K}, therefore providing evidence in favor of the capital-skill complementarity hypothesis in the full sample of 46 countries.[9]

3.4 Estimation results from the OECD and non-OECD subsamples

A motivating factor in using the current dataset and testing approach was that they permit examination of the capital-skill complementarity hypothesis in subsamples of countries by using a reduced form linear equation. As discussed previously, subsample estimation is currently impossible when testing the hypothesis directly from the aggregate production function because it requires a large

[9]Results are qualitatively similar when we use the full Caselli-Colleman sample of 52 countries (see top panel of Table A2 in the appendix).

Table 2: Cross-country regressions for OECD and non-OECD subsamples

OECD

Specification	Model 1	Model 2	Model 3	Model 4
Constant	0.69070**	0.72150***	−1.21129	−1.35479
	(0.24782)	(0.15901)	(0.96537)	(1.04928)
$\ln(w_1/w_2)$	0.05196			0.12475
	(0.30553)			(0.27602)
$\ln(K/Y)$	0.11311	0.09665	−0.12046	−0.08823
	(0.19972)	(0.16562)	(0.18415)	(0.20561)
$\ln Y$			0.21183*	0.21941*
			(0.10479)	(0.11006)
s.e.e.	0.19332	0.19160	0.14376	0.14219
Adj. R^2	0.01	0.02	0.22	0.20
Obs.	15	15	15	15

Non-OECD

Specification	Model 1	Model 2	Model 3	Model 4
Constant	0.40848***	0.42933***	−0.13039	−0.39366
	(0.05705)	(0.03597)	(0.31291)	(0.35705)
$\ln(w_1/w_2)$	0.05492			0.17069
	(0.11715)			(0.12024)
$\ln(K/Y)$	0.28296***	0.29017***	0.22734***	0.18241**
	(0.05998)	(0.05700)	(0.06477)	(0.07113)
$\ln Y$			0.06680*	0.09051**
			(0.03706)	(0.03987)
s.e.e.	0.37005	0.37345	0.33517	0.31189
Adj. R^2	0.45	0.45	0.49	0.52
Obs.	31	31	31	31

Notes: The dependent variable is skilled-labor share of the wage bill (S_1). w_1/w_2 is skilled-unskilled wage premium, K/Y is capital-output ratio and Y is output. Robust standard errors are given in parentheses. 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.

number of observations. In this section, we examine the sensitivity of our findings to two arbitrarily chosen nonoverlapping subsamples of our full sample of 46 countries. In particular, we are interested in examining whether our findings are sensitive to splitting our full sample into OECD and non-OECD subsamples.[10]

Regression estimates from the two subsamples are presented in Table 2. In the OECD subsample, all four models obtain point estimates of γ_{1K} that are not significantly different from zero. Interestingly, from all the relevant variables, only the coefficient for Y is statistically significant (albeit marginally) and takes a positive value as in the full sample. In addition, notice that the Adj. R^2 statistic is very small in the models that do not include the output variable, e.g. Models 1 and 2.

In contrast, in the non-OECD subsample, γ_{1K} estimates vary from 0.18241 (Model 4) to 0.29017 (Model 2) and are significant at the 5% level and 1% level, respectively. Adj. R^2 is quite large in all four models ranging from 0.45 to 0.52. Point estimates of coefficients for w_1/w_2 are insignificantly positive. Even though the coefficient estimates for Y are positive and significant in Models 3 and 4, their magnitudes and significance are a lot lower than in the full sample or the OECD subsample.[11]

The main finding from arbitrarily splitting our full sample into OECD and non-OECD subsamples is that even though there is strong evidence in favor of capital-skill complementarity for the non-OECD subsample, there is no evidence for the OECD subsample. This result has potentially important implications for pinning down the primary determinants of wage inequality and economic growth in the two groups of countries. We discuss some of these implications shortly.

3.5 Threshold estimation

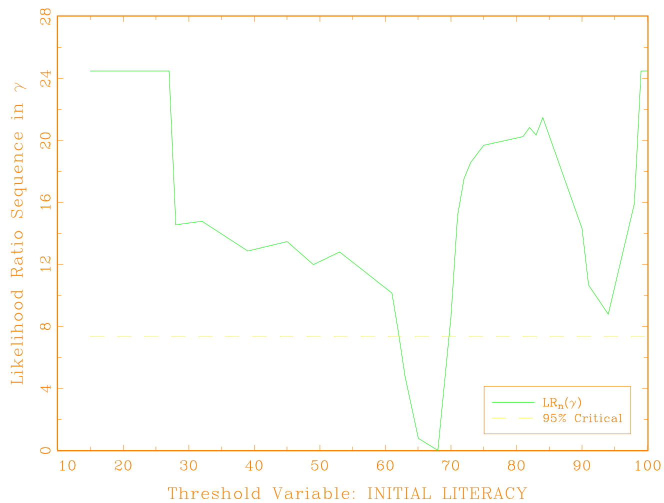
Unlike the previous section in which we arbitrarily split the data into two subsamples, here we follow Hansen (2000) to search for multiple regimes (endogenously determined subsamples) in the data using the skilled-labor share equation (4).[12] Hansen (2000) develops a statistical theory of threshold estimation in the linear regression context that allows for cross-section observations. Least squares estimation is considered, and an asymptotic distribution theory for the regression

[10]Here we follow the vast majority of cross-country empirical literature that arbitrarily splits the data into these two subsamples. The OECD countries are marked with an asterisk in Table A1 in the appendix.

[11]Results are qualitatively similar when we use the full Caselli-Colleman sample of 52 countries (see middle and lower panels of Table A2 in the appendix).

[12]Even though the threshold estimation analysis in this section is based on our basic specification (Model 1), in a subsequent section that is concerned with the robustness of these results, threshold estimation is done using the alternative models (Models 2-4).

Figure 1: First sample split



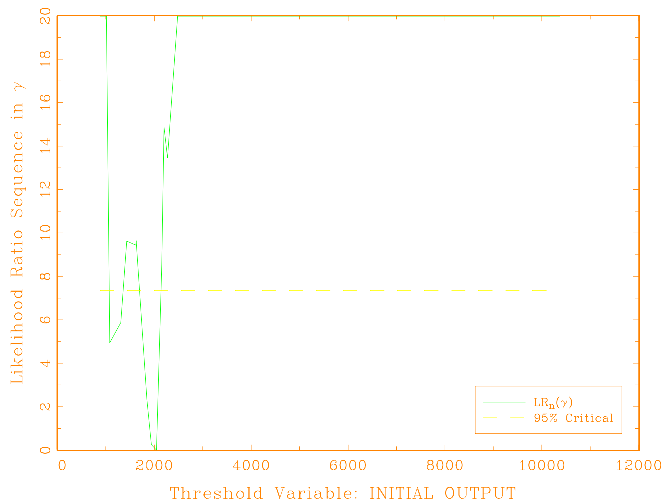
estimates is developed. The main advantage of Hansen's methodology over the regression-tree model (i.e. Durlauf and Johnson (1995)) is that it is based on an asymptotic distribution theory that can formally test the statistical significance of regimes selected by the data.[13] Following recent papers on parameter heterogeneity in regression models, we search for multiple regimes in the data using initial per capita output (y_{60}) and initial adult literacy rates (LIT_{60}) as potential threshold variables.[14]

Since Hansen's statistical theory allows for one threshold for each threshold variable, we proceed by selecting between the two threshold variables using the heteroskedasticity-consistent Lagrange Multiplier test for a threshold developed by Hansen (1996). In the first round of splitting, it is shown that the threshold model using LIT_{60} is significant with p-value of 0.001, whereas y_{60} is insignificant with p-value of 0.437. These results indicate that there exists a sample split based on literacy rates. Figure 1 presents the normalized likelihood ratio sequence $LR_n^*(\gamma)$ statistic as a function of the output threshold. The least-squares estimate γ is the value that minimizes the function $LR_n^*(\gamma)$ which occurs at $\hat{\gamma} = 68\%$. The asymptotic 95% critical value (7.35) is shown by the dotted line and where it crosses $LR_n^*(\gamma)$ displays the confidence set $[63\%, 68\%]$. The LIT_{60}

[13]For a detailed discussion of the statistical theory for threshold estimation in linear regressions, see Hansen (2000) and Caner and Hansen (forthcoming).

[14]These two possible threshold variables are considered to be good proxies for initial endowment. We acknowledge that other potential threshold variables can be used to further investigate nonlinearities in capital-skill complementarity. We leave this investigation for future research.

Figure 2: Second sample split



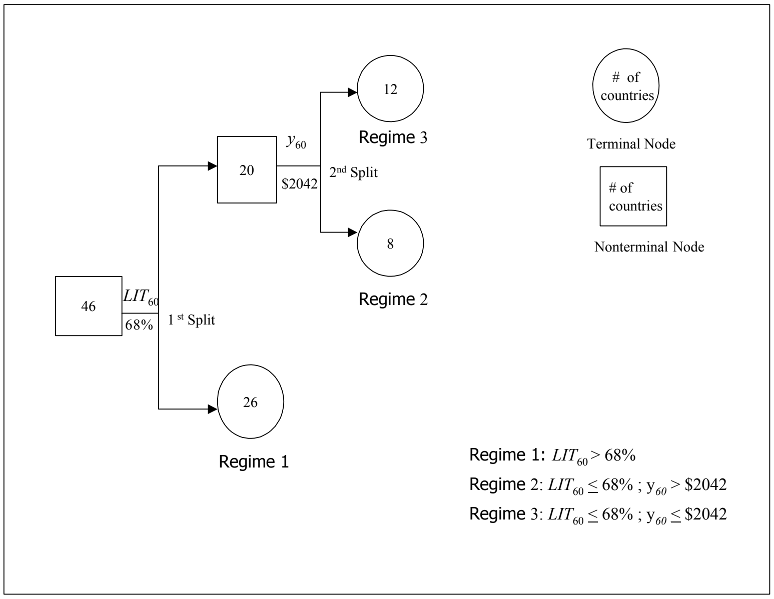
threshold variable divides our full sample of 46 countries into a low-literacy group (below 68%) with 20 countries and a high-literacy group (above 68%) with 26 countries.

Further splitting of the high-literacy group is not possible according to the bootstrap test statistic. However, we find that further splitting of the low-literacy subsample (of 20 countries with initial literacy rate below 68%) is possible. The threshold model using initial output (y_{60}) is significant attaining a p-value of 0.021.[15] Figure 2 presents the normalized likelihood ratio statistic as a function of the output threshold. The point estimate for the literacy threshold is $\hat{\gamma} = \$2042$ with the 95% confidence interval $[\$1077, \$2042]$. The output threshold variable splits the low-literacy subsample of 20 countries into two additional regimes; the low-literacy-low-output regime with 12 countries and the low-literacy-high-output regime with 8 countries. No further splitting was possible for the two regimes as bootstrap test statistics were insignificant.

Figure 3 presents a regression tree diagram that illustrates our threshold estimation results obtained under the skilled-labor share equation (4). Non-terminal nodes are illustrated by squares whereas terminal nodes are illustrated by circles. The numbers inside the squares and circles show the number of countries in each node. The point estimates for each threshold variable are presented on the rays connecting the nodes. As shown in Figure 3, the threshold analysis reveals

[15] Notice that in threshold models, sample spliting beyond the first sample split is conditional on the previous sample splits. Consequently, in our exercise, the second sample split (using y_{60}) is conditional on the first sample split (using LIT_{60}).

Figure 3: Regression tree obtained using thresohold estimation



that there exist three regimes that obey different statistical models with distinctly different capital-skill complementarities. Regime 1 contains countries with relatively high literacy rates (above 68%) whereas Regime 3 contains countries with low literacy rates (below 68%) and low incomes (below $2042). Finally Regime 2 consists of countries with quite low literacy rates (below 68%) but with respectable per capital incomes (above $2042). Table 3 presents the countries in each regime obtained from our threshold estimation.

3.6 Estimation results from the three regimes

To further investigate the nonlinearity in capital-skill complementarity across countries obtained from the Hansen (2000) endogenous threshold methodology, we turn attention to estimation of the regression coefficients of equation (4) for the three regimes. Table 4 presents these coefficient estimates.

Notice that estimates vary extensively in magnitude and significance across regimes, therefore providing strong support in favor of parameter heterogeneity and the presence of multiple regimes. For example, in Model 1, point estimates of γ_{1K} vary from 0.14073 (significant at the 5% level)

Table 3: Country classification

Regime 1		Regime 2	Regime 3
Argentina	Nicaragua	Colombia	Bolivia
Australia	Panama	Ecuador	Brazil
Canada	Paraguay	Guatemala	Dom. Rep.
Chile	Philippines	Malaysia	El Salvador
Costa Rica	S. Korea	Mexico	Ghana
France	Singapore	Peru	Honduras
Greece	Sri Lanka	Portugal	India
Hong Kong	Sweden	Venezuela	Indonesia
Israel	Switzerland		Kenya
Italy	U.K.		Pakistan
Jamaica	U.S.A.		Thailand
Japan	Uruguay		Tunisia
Netherlands	W. Germany		
(26)		(8)	(12)

in Regime 3, to 0.37026 (significant at the 1% level) in Regime 2. In addition, point estimates of coefficients for $\ln(w_1/w_2)$ vary from -0.02802 (not significantly different from zero) in Regime 1, to 0.58133 (significant at the 1% level) in Regime 2. Substantial variation of parameters across the three regimes is also evident in Models 2-4.

More importantly, our results reveal that capital-skill complementarity is more pronounced in Regime 2 (middle-income low-education subsample), than in Regime 1 (high education subsample) or Regime 3 (low-income low-education subsample). In particular, in Model 1 coefficient estimates of γ_{1K} are 0.21015 and 0.14073 (and significant at the 5% level) in Regimes 1 and 3, respectively, whereas in Regime 2 is 0.37026 (significant at the 1% level). Robustness analysis of our baseline Model 1 shows that our result is indeed reinforced when we consider the alternative Models 2-4. For example, in Models 3-4 (that include Y) the relevant coefficient γ_{1K} becomes insignificant for Regime 1 and marginally significant for Regime 3, whereas it is amplified in magnitude and remains highly significant for Regime 2. Every model considered here shares the same nonlinearity in capital-skill complementarity with Regime 2 experiencing the most pronounced effect.

A few other points are worth noting. First, in all but one model (Model 1 in Regime 1) the coefficient for w_1/w_2 is positive and significant providing evidence that the elasticity of substitution between skilled and unskilled labor is less than unity, and therefore quite complementary. Second, inclusion of Y in our baseline model enters positively significant only in Regime 1 (see Models 3-4).

Table 4: Cross-country regressions for the three regimes

Cross-country regressions for Regime 1

Specification	Model 1	Model 2	Model 3	Model 4
Constant	0.60515***	0.59562***	−0.20956	−0.79783*
	(0.08873)	(0.07664)	(0.31882)	(0.42407)
$\ln(w_1/w_2)$	−0.02802			0.26924*
	(0.12269)			(0.13562)
$\ln(K/Y)$	0.21015**	0.20950**	0.07775	−0.00919
	(0.09003)	(0.08830)	(0.09458)	(0.09989)
$\ln Y$			0.09458**	0.15293***
			(0.03656)	(0.04552)
s.e.e.	0.35734	0.35834	0.27940	0.24079
Adj. R^2	0.17	0.17	0.33	0.41
Obs.	26	26	26	26

Cross-country regressions for Regime 2

Specification	Model 1	Model 2	Model 3	Model 4
Constant	0.09491	0.46748***	0.83075	0.58137
	(0.12019)	(0.05099)	(0.67219)	(0.38798)
$\ln(w_1/w_2)$	0.58133***			0.60174**
	(0.18062)			(0.17191)
$\ln(K/Y)$	0.37026***	0.21045***	0.22678**	0.39833***
	(0.06589)	(0.06893)	(0.07851)	(0.06615)
$\ln Y$			−0.04041	−0.05556
			(0.07453)	(0.04243)
s.e.e.	0.00640	0.01857	0.01757	0.00465
Adj. R^2	0.80	0.51	0.49	0.83
Obs.	8	8	8	8

Cross-country regressions for Regime 3

Specification	Model 1	Model 2	Model 3	Model 4
Constant	0.27942***	0.39655***	0.41730	0.08836
	(0.05522)	(0.03180)	(0.45210)	(0.39736)
$\ln(w_1/w_2)$	0.29561**			0.31099**
	(0.12496)			(0.13484)
$\ln(K/Y)$	0.14073**	0.19574**	0.19769*	0.12049
	(0.06196)	(0.07420)	(0.08559)	(0.07741)
$\ln Y$			−0.00252	0.02251
			(0.05490)	(0.04633)
s.e.e.	0.04080	0.07218	0.06490	0.03936
Adj. R^2	0.57	0.27	0.34	0.55
Obs.	12	12	12	12

Notes: The dependent variable is skilled-labor share of the wage bill (S_1). w_1/w_2 is skilled-unskilled wage premium, K/Y is capital-output ratio and Y is output. Robust standard errors are given in parentheses. 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 5: J test: Model 1 vs. Model 3

Specification	Model 1	Model 3
Test Statistic (p-value)	**4.00877** (**0.00020**)	−1.59141 (0.11900)

Notes: Models 1 and 3 are the only two non-nested models. Bold values indicate significance at the 5% level.

This may suggest that the production function in developed countries is non-homothetic. Third, the Adj. R^2 statistic is the highest for models in Regime 2, and lowest for models in Regime 1. This may suggest that our proposed models for testing the capital-skill complementarity hypothesis better fit the experience of developing countries than that of developed countries. Finally, a qualification is in place here. Even though we use bootstrap techniques to account for estimation in small samples, our results should be interpreted with some caution since ultimately we use these small samples to provide guidance to economic theories.[16]

4 Robustness

In this section we examine the robustness of the results to alternative functional forms. In addition to testing the robustness of our empirical findings using different linear and nonlinear regression model specifications, we have also reconsidered our findings for alternative subsamples of countries.[17]

4.1 Alternative functional forms

We start by employing econometric tests for non-nested linear regression model selection (J-type tests), and functional form (RESET tests).

J tests for non-nested linear regression models

A careful look at the results from the whole sample in Table 1, reveals that Model 3 possibly dominates Model 1. Given that Models 1 and 3 are non-nested we can more formally test this

[16] In the next section, we also consider two rather than three regimes obtained after the first split. In this case, Regimes 2 and 3 are merged which increases the sample size to 20 observations.

[17] We are grateful to an anonymous referee for extremely valuable comments on robustness analyses of our baseline results.

assertion, by employing a J test for non-nested linear regression models.[18] The Test Statistic for Model i is the t-statistic of fitted dependent variables from Model j, where $i, j = 1, 3$. We reject Model i if the Test Statistic for Model i is significant.

Results from such test appear in Table 5. The J test performed on the full sample of 46 countries does not reject Model 3 but rejects Model 1. Thus consistent with our assertion, Model 3 dominates Model 1 indicating that including $\ln Y$ and excluding $\ln(w_1/w_2)$ improves the fit of the estimated specification.

RESET tests for functional form

In this section we perform RESET tests for functional form of our estimated equations. In particular, we add nonlinear (quadratic and cubic functions) functions of $\ln(K/Y)$ and $\ln Y$ in all four models considered in our baseline estimation. These tests are motivated from the observation that the addition of $\ln Y$ improves considerably the fit of these equations. This in turn implies that $\ln K$ and $\ln Y$ may not share the same coefficient or that the $\ln(K/Y)$ term enters nonlinearly.

For clarity and ease of exposition, we report RESET test results only for Model 3 in the main text. These results are presented in Table 6. RESET test results for Models 1, 2 and 4 are presented in Tables A3, A4 and A5, respectively, in the appendix. The Null Hypothesis is that additional variables of the *Specified Model* jointly equal to zero. p-values (in parentheses) in bold indicate significance at the 5% level. To reduce the computational cost associated with bootstrapping in the numerous specifications considered in the robustness analysis, we do not report robust standard errors but instead p-values for normal distributions. Experimentation with the bootstrap revealed that the robust and normal standard errors were very similar.

The RESET tests for functional form indicate that adding the nonlinear terms $\ln(K/Y)]^2$, $[\ln(K/Y)]^3$, $(\ln Y)^2$, $(\ln Y)^3$, and combinations thereof, to our original set of explanatory variables, does not improve the significance of Models 3 and 4 (see RESET test results in Tables 6 and A5, respectively). In contrast, these tests show that the nonlinear terms improve Model 1 and Model 2 significantly (see RESET test results in Tables A3 and A4, respectively, in the appendix). In general, however, Model 4 is shown to dominate both Model 1 and Model 2 (see second row of Table A3 and fourth row of Table A4, respectively), Model 3 dominates Model 2 (see third row of Table A4), implying potential non-homotheticity of the production function.[19] Finally, comparing

[18] Notice that out of the four models considered only Models 1 and 3 are non-nested.

[19] RESET tests can not compare Model 1 and Model 3. Recall, however, that using a J test we have shown that

Table 6: RESET tests: Model 3 vs. specified model

Specification	Test Statistic (p-value)
$\ln(w_1/w_2), \ln(K/Y), \ln Y$ [Model 4]	2.77201 (0.10337)
$\ln(w_1/w_2), \ln(K/Y), \ln Y, \ln[(K/Y)]^2$	1.64175 (0.20612)
$\ln(w_1/w_2), \ln(K/Y), \ln Y, (\ln Y)^2$	2.29676 (0.11339)
$\ln(w_1/w_2), \ln(K/Y), \ln Y, (\ln Y)^3$	2.32786 (0.11026)
$\ln(w_1/w_2), \ln(K/Y), \ln Y, [\ln(K/Y)]^2, (\ln Y)^2$	1.49528 (0.23047)
$\ln(w_1/w_2), \ln(K/Y), \ln Y, [\ln(K/Y)]^2, [\ln(K/Y)]^3$	1.25999 (0.30106)
$\ln(w_1/w_2), \ln(K/Y), \ln Y, (\ln Y)^2, [\ln(K/Y)]^3$	1.50949 (0.22677)
$\ln(w_1/w_2), \ln(K/Y), \ln Y, [\ln(K/Y)]^2, (\ln Y)^3$	1.51510 (0.22532)
$\ln(w_1/w_2), \ln(K/Y), \ln Y, (\ln Y)^2, (\ln Y)^3$	1.68552 (0.18547)
$\ln(w_1/w_2), \ln(K/Y), \ln Y, [\ln(K/Y)]^2, \ln Y, \ln[(K/Y)]^3$	1.22148 (0.31740)
$\ln(w_1/w_2), \ln(K/Y), \ln Y, [\ln(K/Y)]^2, (\ln Y)^2, (\ln Y)^3$	1.23698 (0.31116)
$\ln(w_1/w_2), \ln(K/Y), \ln Y, [\ln(K/Y)]^2, [\ln(K/Y)]^3, (\ln Y)^3$	1.24182 (0.30924)
$\ln(w_1/w_2), \ln(K/Y), \ln Y, (\ln Y)^2, [\ln(K/Y)]^3, (\ln Y)^3$	1.25158 (0.30539)
$\ln(w_1/w_2), \ln(K/Y), \ln Y, [\ln(K/Y)]^2, (\ln Y)^2, [\ln(K/Y)]^3, (\ln Y)^3$	1.22497 (0.31641)
$\ln(K/Y), \ln Y, [\ln(K/Y)]^2$	0.28851 (0.59401)
$\ln(K/Y), \ln Y, (\ln Y)^2$	0.97930 (0.32804)
$\ln(K/Y), \ln Y, (\ln Y)^3$	1.02055 (0.31817)
$\ln(K/Y), \ln Y, [\ln(K/Y)]^2, (\ln Y)^2$	0.47822 (0.62330)
$\ln(K/Y), \ln Y, [\ln(K/Y)]^2, [\ln(K/Y)]^3$	0.35046 (0.70645)
$\ln(K/Y), \ln Y, (\ln Y)^2, [\ln(K/Y)]^3$	0.50121 (0.60946)
$\ln(K/Y), \ln Y, [\ln(K/Y)]^2, (\ln Y)^3$	0.49820 (0.61126)
$\ln(K/Y), \ln Y, (\ln Y)^2, (\ln Y)^3$	0.73024 (0.48795)
$\ln(K/Y), \ln Y, [\ln(K/Y)]^2, (\ln Y)^2, (\ln Y)^3$	0.47733 (0.69985)
$\ln(K/Y), \ln Y, [\ln(K/Y)]^2, (\ln Y)^2, [\ln(K/Y)]^3$	0.43334 (0.73029)
$\ln(K/Y), \ln Y, [\ln(K/Y)]^2, [\ln(K/Y)]^3, (\ln Y)^3$	0.45079 (0.71814)
$\ln(K/Y), \ln Y, (\ln Y)^2, [\ln(K/Y)]^3, (\ln Y)^3$	0.49941 (0.68481)
$\ln(K/Y), \ln Y, [\ln(K/Y)]^2, (\ln Y)^2, [\ln(K/Y)]^3, (\ln Y)^3$	0.59577 (0.66781)

Notes: The Null Hypothesis is that additional variables of Specified Model jointly equal to 0. The dependent variable is skilled-labor share of the wage bill (S_1). All of the specifications above were run with a constant. p-values are given in parentheses. Bold values indicate significance at the 5% level.

Models 3 and 4 by looking at the results in Table 1 does not provide a clear answer as to which of the two models is more appropriate for our full sample estimation. More specifically, although the Adj. R^2 is slightly higher for Model 4 than Model 3, the coefficient for $\ln(w_1/w_2)$ in Model 4 is insignificant, although marginally as the p-value is only slightly over 0.10 which. This is also confirmed by the RESET tests (see second row of Table 6).

In summary, our econometric tests for functional form provide support for specifications that include the term $\ln Y$ (Models 3 and 4) implying potential non-homotheticity of the production function. In addition, RESET test results show that the inclusion of nonlinear terms, such as $(\ln Y)^2$ and $[\ln(K/Y)]^2$, do not improve significantly these preferred specifications. This would suggest that the nonlinearity in capital-skill complementarity is not due to the aggregate specification but rather due to parameter heterogeneity. Put differently, the nonlinearity is due to different regimes of countries obeying different statistical models.

4.2 Alternative subsamples

Next, we test for subsample structural differences (Chow-type tests), and perform threshold estimation using alternative models to our basic specification (Model 1).

Threshold estimation using alternative models

This section examines the robustness of our baseline threshold results by considering alternative subsamples and models. Given the small number of observations in Regimes 2 and 3 (8 and 12, respectively), we re-estimate Models 1-4 in section 3.6 after only the first round of splitting based on literacy rates. This obtains Regime 1 with high literacy rates (above 68%; 26 countries) and the combination of Regimes 2 and 3 (call it Regime 2a) with low literacy rates (below 68%; 20 countries). Since we have already described results for Regime 1 (see upper panel of Table 3) we focus attention to coefficient estimates for the new Regime 2a presented in Table 7.

For Regime 2a point estimates of coefficients on $\ln(w_1/w_2)$ in Model 1 and Model 4 are significantly positive at 5%. More importantly, the estimate of γ_{1K} is significantly positive at 1% in all models, ranging from 0.21217 in Model 4 to 0.25156 in Model 1, thus providing strong evidence of capital-skill complementarity. Although these estimates are quite close to those in Models 1 and 2 for Regime 1, Chow tests (see below) reject no structural change between Regime 1 and Regime 2a

Model 3 dominates Model 1.

Table 7: Cross-country regressions for Regime 2a (consisting of Regimes 2&3)

Specification	Model 1	Model 2	Model 3	Model 4
Constant	0.29245***	0.40084***	0.14665	−0.01389
	(0.05341)	(0.02734)	(0.31765)	(0.29299)
$\ln(w_1/w_2)$	0.24797**			0.25739**
	(0.10929)			(0.10977)
$\ln(K/Y)$	0.25156***	0.25774***	0.22477***	0.21217***
	(0.04196)	(0.04766)	(0.06223)	(0.05596)
$\ln Y$			0.03066	0.03645
			(0.03816)	(0.03424)
s.e.e.	0.08201	0.11115	0.10145	0.07682
Adj. R^2	0.68	0.56	0.60	0.69
Obs.	20	20	20	20

Notes: The dependent variable is skilled-labor share of the wage bill (S_1). w_1/w_2 is skilled-unskilled wage premium, K/Y is capital-output ratio and Y is output. Robust standard errors are given in parentheses. 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.

for all models. Finally, notice that Adj. R^2 is relatively higher for models not including $\ln(w_1/w_2)$; namely 0.68 in Model 1 and 0.69 in Model 4.

Next, we examine the robustness of our threshold results by considering in addition to our basic specification (Model 1), the alternative specifications (Models 3 and 4) favored by our functional form tests presented above. The key finding here is that regardless of whether we use Model 3 or Model 4 we obtain the same terminal literacy threshold of 65% that is very close to the literacy threshold of 68% obtained using Model 1. The high-literacy regime now includes 28 countries (call this Regime 1b) whereas the low-literacy regime includes 18 countries (call this Regime 2b). Ecuador and Thailand are the two countries that move out from the low and into the high literacy regime.

Results from this exercise are presented in Table 8. One can readily verify that coefficient estimates are very similar to those in the upper panel of Table 3 for Regime 1, and Table 7 for Regime 2a. In our threshold estimation robustness analysis, we have also considered all four models with the nonlinear terms $(\ln Y)^2$ and $[\ln(K/Y)]^2$. Results varied slightly with estimation but the terminal threshold variable was always literacy of 65% or 68% consistent with our previous results.[20]

[20]These results are available from the authors upon request.

Table 8: Cross-country regressions for two alternative regimes

Cross-country regressions for Regime 1b

Specification	Model 1	Model 2	Model 3	Model 4
Constant	0.58103***	0.57057***	−0.23594	−0.81613*
	(0.08341)	(0.07012)	(0.29880)	(0.39968)
$\ln(w_1/w_2)$	−0.02904			0.26999*
	(0.12090)			(0.13146)
$\ln(K/Y)$	0.22988***	0.22977***	0.09673	−0.01521
	(0.08326)	(0.08188)	(0.08775)	(0.09236)
$\ln Y$			0.09523***	0.15232***
			(0.03459)	(0.04298)
s.e.e.	0.38214	0.38387	0.29028	0.24806
Adj. R^2	0.21	0.21	0.38	0.46
Obs.	28	28	28	28

Cross-country regressions for Regime 2b

Specification	Model 1	Model 2	Model 3	Model 4
Constant	0.29171***	0.40043***	0.09663	−0.07265
	(0.05368)	(0.02751)	(0.32118)	(0.28980)
$\ln(w_1/w_2)$	0.24882**			0.25983**
	(0.10884)			(0.10780)
$\ln(K/Y)$	0.23646***	0.24423***	0.20324***	0.18755***
	(0.04391)	(0.04917)	(0.06588)	(0.05793)
$\ln Y$			0.03667	0.04340
			(0.03862)	(0.03391)
s.e.e.	0.07204	0.09499	0.09017	0.06493
Adj. R^2	0.66	0.57	0.58	0.68
Obs.	18	18	18	18

Notes: The dependent variable is skilled-labor share of the wage bill (S_1). w_1/w_2 is skilled-unskilled wage premium, K/Y is capital-output ratio and Y is output. Robust standard errors are given in parentheses. 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 9: Chow tests

OECD and non-OECD

Specification	Model 1	Model 2	Model 3	Model 4
Test Statistic	**2.84171**	**4.42299**	1.50363	0.93665
(p-value)	(**0.04983**)	(**0.01807**)	(0.22829)	(0.45319)

Regimes 1, 2 and 3

Specification	Model 1	Model 2	Model 3	Model 4
Test Statistic	**4.25145**	**8.90347**	1.15138	**3.19421**
(p-value)	(**0.00236**)	(**0.00003**)	(0.35289)	(**0.00822**)

Regimes 1 and 2a

Specification	Model 1	Model 2	Model 3	Model 4
Test Statistic	**7.40761**	**9.59760**	**5.32458**	**5.42105**
(p-value)	(**0.00046**)	(**0.00037**)	(**0.00350**)	(**0.00149**)

Notes: Top panel null hypothesis: OECD and non-OECD structurally not different. Middle panel null hypothesis: Regimes 1, 2 and 3 structurally not different. Bottom panel null hypothesis: Regimes 1 and 2&3 combined structurally not different. Bold values indicates rejection of the null at the 5% level. Regime 2a is Regimes 2 and 3 combined.

Chow tests for structural change

Finally, we perform Chow tests to examine whether our arbitrarily chosen subsamples (OECD and non-OECD) and endogenously determined regimes (Regimes 1, 2 and 3) are structurally different from each other. Results from these robustness analyses are presented in Table 9.

The top panel of Table 9 presents test results for structural change between OECD and non-OECD countries. The Chow test rejects no structural change if we use Models 1 and 2 but does not reject if we use Models 3 and 4. This indicates that for the preferred Models 3 and 4 we should not have trivially split our full sample into OECD and non-OECD. This result is consistent with our subsequent search for endogenous splitting of the full sample into regimes that obey different statistical models.

We have also tested for structural change between the three different endogenously determined regimes using Hansen's (2000) methodology. The middle panel of Table 9 presents results for structural change in the three regimes. The Chow test rejects no structural change if we use Models 1, 2 and 4 but it does not reject if we use Model 3. The justification could be that for Model 3 the significance of coefficients is quite low in all four models, thus rendering regimes not be structurally different. The bottom panel of Table 9 presents Chow test results for Regime 1 and Regime 2a (combining Regimes 2 and 3). It is clearly shown that all four models reject no structural change. This is quite important for the robustness analysis using different threshold models presented in the previous section.

In summary, the extensive robustness analyses concerning alternative threshold models and subsamples shows that, consistent with our baseline results, there is strong evidence of nonlinearities in capital-kill complementarity.

5 Discussion

Our main results can be summarized as follows: First, in the full sample we find evidence in favor of capital-skill complementarity in all four models considered. Second, when we arbitrarily split our full sample into OECD and non-OECD subsamples, we find that the null of capital-skill complementarity hypothesis is rejected in the OECD subsample, but is not rejected in the non-OECD subsample. Third, when we employ Hansen's (2000) data-sorting methodology we find evidence in favor of nonlinearities in capital-skill complementarity and the presence of three regimes that obey distinctly different statistical models. An extensive sensitivity analysis shows that in general these results are quite robust to a battery of econometric tests, alternative testable specifications and threshold models.

What are the implications of these results to the existing literature? Our first result (on the full sample) is qualitatively consistent with but a lot stronger than Duffy, Papageorgiou and Perez-Sebastian (2004) who find some (albeit weak) evidence in favor of capital-skill complementarity using a panel dataset of 73 countries over the period 1965-1990. Perhaps this is due to data differences, as we use cross-sectional data and they use panel data, but most likely our stronger results are due to estimation. In particular, the nature of our dataset (cross-sectional) permits use of linear reduced form regression equations to test the hypothesis, whereas their dataset (panel) is used for nonlinear estimation of aggregate production function parameters. As Duffy, Papageorgiou and Perez-Sebastian show, trying to estimate a second order relationship (such as elasticities of substitution) directly from a highly nonlinear aggregate production function (such as a two-level CES function) is quite difficult and may result in imprecise estimates.

Our second result (on the OECD and non-OECD subsamples) suggests that there is no evidence in favor of capital-skill complementarity for the OECD subsample. This is relevant to the recent literature which tries to explain the rising wage and income inequality in the U.S. and other developed countries due solely to capital-skill complementarity (see, e.g. Krusell et al. (2000)). Our finding points to alternative explanations for rising wage and income inequality in OECD countries, for example, skill-biased technological change as recently argued by Ruiz-Arranz (2002). In addition, our second result suggests that capital is highly complementary to skilled labor in the non-OECD subsample. This maybe because, unlike the OECD countries in which skill is more complementarity to technology, in the non-OECD countries skill is more productive when it complements capital (that presumably is more accessible than technology).

Our final result is perhaps the most striking. We find that capital-skill complementarity is a phenomenon that does not share equal support across countries. In particular, we find that in Regime 2 (8 middle-income-low-literacy countries) exhibits substantially higher level of capital-skill complementarity than Regime 3 (12 low-income-low-literacy countries) and Regime 1 (26 high-literacy countries). The parameter heterogeneity evident in our cross-country regressions and the resulting nonlinearity in the development process regarding the capital-skill complementarity hypothesis relates to and is consistent with the parameter heterogeneity found in cross-country growth regressions (see e.g., Liu and Stengos (1999), Durlauf (2001), and Kalaitzidakis et al. (2001)). More importantly, this finding is qualitatively consistent with Goldin and Katz who show that, in the U.S. manufacturing, capital-skill complementarity was at least as large for the period 1909-1919 as for the period 1979-1989 and significantly larger than for the period 1959-1979 (see Goldin and Katz (1998, pp. 722-723)). Both ours and Goldin and Katz's results suggest that it maybe misleading to think of capital-skill complementarity as a universal phenomenon. In contrast, our results suggest that the complementarity between capital and labor may vary across time and countries.

Extensive robustness analyses were performed focusing primarily on alternative functional forms of the baseline specification, and alternative subsamples of countries. These analyses obtained the following two main results: First, our baseline empirical findings were shown to be quite robust to alternative functional forms and subsamples obtained from alternative threshold models. Second, the robustness results suggest that the nonlinearity in capital-skill complementarity is not due to the aggregate specification but due to parameter heterogeneity. That is, the nonlinearity is due to parameters of our linear regression specifications not being constant across countries.

A clear message from our findings is that to further understand the behavior of the nonlinear relationship between capital-skill complementarity and the development process, a theory is needed. Here we suggest a model in which capital-skill complementarity nonlinearities, of the sort obtained in this paper, are the endogenous outcome of the economic system. Assume that the world consists of low, middle and high-income countries. A social planner chooses how to use physical capital, technology, and skilled and unskilled labor to maximize agents' utility function. Assume that poor countries are poorly educated and rich countries are well-educated. Poor countries choose to allocate their scare stock of capital to complement their abundant stock of unskilled labor, therefore rendering capital-skill complementarity a second-order phenomenon. On the other hand, rich countries, which have wide access to technology, choose to allocate most of their plentiful skilled labor to the technology sector, also rendering capital-skill complementarity a second-order phenomenon. Where capital-skill complementarity is most pronounced is in the middle-income countries with *some* skilled labor. Assuming that in these countries physical capital stock is more abundant than technology, then it is more productive to allocate their scarce skilled labor to complement physical capital.

6 Conclusion

In this paper we have used a novel dataset to test Griliches' capital-skill complementarity hypothesis in a cross-section of countries. Our main result is threefold: First we find evidence in favor of the hypothesis in our full sample of 46 countries. Second, when we arbitrarily split the data into OECD and non-OECD subsamples, we find that the hypothesis is not supported for the OECD countries but strongly supported for the non-OECD countries. Third, using Hansen's (2000) data-splitting methodology we find evidence in favor of parameter heterogeneity and nonlinearities in capital-skill complementarity. In particular, we find that capital-skill complementarity is most pronounced in middle-income countries. These results are quite robust to a range of sensitivity analyses.

Our findings call for further investigation of capital-skill complementarity, as empirical support of the hypothesis would have important implications in specifying the aggregate production function and therefore in re-evaluating existing empirical and theoretical findings. Beyond the possible nonlinearity in capital-skill complementarity across the development process, equally intriguing is the possible nonlinearity of the phenomenon in the short run and the long run. The idea, originally explored in Galor and Moav (2000) and Galor and Weil (2000), is that capital may benefit skilled labor in the short run due to the comparative advantage of educated individuals to cope with a changing technological environment. This effect may occur regardless of whether in the long run capital is skilled-biased or unskilled-biased. Even though the dataset used here is not fit to distinguish between short run and long run, it would be a real advancement if future work could take on this issue. Finally, this paper was a first attempt towards understanding how pronounced capital-skill complementarity is in different groups of countries. Future work focused on the magnitude of the complementarity between skilled labor and capital will shed new light on the evolution of distributive shares, a central component of policy analysis.

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Appendix

We follow Brown and Christensen (1981) in deriving the skilled-labor share equation of a quasi-fixed cost function. Assume that output (Y) is produced using capital (K), which is a quasi-fixed factor, and skilled labor (L_1) and unskilled labor (L_2), which are variable factors. Then the translog *variable cost function* is defined as

$$\begin{aligned}\ln C^v \quad = \quad & \alpha_0 + \alpha_1 \ln w_1 + \alpha_2 \ln w_2 + \alpha_K \ln K + \alpha_Y \ln Y + \\ & 1/2(\gamma_{11} \ln w_1^2 + \gamma_{12} \ln w_1 \ln w_2 + \gamma_{21} \ln w_2 \ln w_1 + \gamma_{22} \ln w_2^2) + \\ & 1/2\gamma_{KK}(\ln K)^2 + 1/2\gamma_{YY}(\ln Y)^2 + \gamma_{1K} \ln w_1 \ln K + \gamma_{2K} \ln w_2 \ln K + \\ & \gamma_{1Y} \ln w_1 \ln Y + \gamma_{2Y} \ln w_2 \ln Y + \gamma_{KY} \ln K \ln Y, \end{aligned} \tag{A1}$$

where C^v denotes the variable cost, w_1 is the price of skilled labor, and w_2 is the price of unskilled labor.

Assuming cost minimizing price taking behavior, the conditional demand of variable inputs (L_i, where $i = 1, 2$) can be written by the Shepard's lemma as

$$L_i = \frac{\partial C^v}{\partial w_i}. \tag{A2}$$

It then follows that the share of the i^{th} input, L_i, in the variable cost function is defined (using A2) as

$$S_i = \frac{w_i L_i}{C^v} = \frac{\frac{1}{C}\frac{\partial C^v}{\partial w_i}}{\frac{1}{w_i}} = \frac{\partial \ln C^v}{\partial \ln w_i}. \tag{A3}$$

Using equations (A1) and (A3) yields the share of skilled labor in the variable cost function as

$$S_1 = \alpha_1 + \ \gamma_{11} \ln w_1 + \gamma_{12} \ln w_2 + \gamma_{1K} \ln K + \gamma_{1Y} \ln Y. \tag{A4}$$

Finally, we make the following two theoretical assumptions: First, we impose linear homogeneity in input prices which means that for a fixed level of output total cost increases proportionally when all prices increase proportionally. This assumption implies the following linear restrictions: $\alpha_1 + \alpha_2 = 1$, $\gamma_{11} + \gamma_{21} = \gamma_{11} + \gamma_{12} = \gamma_{12} + \gamma_{22} = \gamma_{21} + \gamma_{22} = 0$, $\gamma_{1Y} + \gamma_{2Y} = \gamma_{1K} + \gamma_{2K} = 0$. Second, we impose constant returns to scale to the production function which implies the following additional restrictions: $\alpha_K + \alpha_Y = 0$, $\gamma_{1K} + \gamma_{1Y} = \gamma_{2K} + \gamma_{2Y} = 0$, $\gamma_{KK} + \gamma_{KY} = \gamma_{KY} + \gamma_{YY} = 0$. The imposition of linear homogeneity in input prices and constant returns to scale in equation (A1) yields the estimation equation (4) in the main text for the skilled labor share of total labor costs

$$S_1 = \alpha_1 + \gamma_{11} \ln(w_1/w_2) + \gamma_{1K} \ln(K/Y).$$

Table A1: Values of relevant variables (52 countries)

Country	Regression Equation Variables						Threshold Var.	
	$(Y/L)_{88}$	$(K/L)_{88}$	L_1	L_2	w_1/w_2	S_1	$(Y/L)_{60}$	$(Lit.)_{60}$
Argentina	14804.7	33151.4	106.45	59.90	1.51	0.729	4852	91
Australia*	29858.1	88075.5	128.79	17.08	1.24	0.903	8440	100
Bolivia	4952.5	9076.4	50.74	74.91	1.33	0.474	1618	39
Botswana†	3315.8	9884.9	40.73	115.07	2.15	0.432	—	—
Brazil	11297.0	21226.6	61.97	99.61	1.80	0.528	1842	61
Canada*	33336.9	82442.8	133.70	7.04	1.23	0.959	10286	99
Chile	9323.1	22451.9	107.74	72.64	1.62	0.706	5189	84
China†	2123.7	4156.4	49.85	64.89	1.22	0.484	—	—
Colombia	9360.2	15433.7	76.09	83.39	1.75	0.615	2672	63
Costa Rica	9118.2	16695.3	76.78	82.61	1.55	0.590	3360	90
Cyprus†	15804.7	37046.2	143.77	47.87	1.55	0.823	—	—
Dom. Rep.	7314.3	12231.8	48.74	84.97	1.46	0.456	1939	65
Ecuador	8388.1	21190.1	106.87	68.52	1.60	0.714	2198	68
El Salvador	5548.5	5617.3	38.05	92.26	1.47	0.377	2042	49
France*	28971.6	84929.0	111.70	45.53	1.49	0.785	7215	99
Ghana	1853.9	1217.9	35.24	83.85	1.40	0.370	1009	27
Greece*	16607.3	42802.4	85.39	26.54	1.11	0.781	2257	81
Guatemala	7430.5	7772.6	43.36	98.19	1.81	0.444	2481	32
Honduras	4596.5	6174.7	74.94	102.17	2.02	0.597	1430	45
Hong Kong	21532.3	29127.6	98.99	38.21	1.28	0.768	3085	70
Hungary*†	10868.9	33857.0	88.94	37.43	1.19	0.739	—	—
India	3045.7	3775.5	34.47	79.29	1.22	0.347	978	28
Indonesia	3914.3	8083.8	72.29	84.62	1.97	0.627	879	39
Israel	23362.3	51767.6	118.69	36.53	1.29	0.807	4802	84
Italy*	29552.4	82317.6	66.22	42.94	1.10	0.629	4913	91
Jamaica	4595.5	12830.9	184.72	96.17	3.16	0.859	2726	82
Japan*	20807.3	64180.8	119.16	27.87	1.30	0.848	3493	98
Kenya	1997.8	2748.3	34.46	108.77	1.93	0.379	944	20
Malaysia	9471.6	23542.7	81.76	58.80	1.46	0.670	2154	53
Mexico*	15329.6	28448.8	92.07	81.22	1.76	0.666	4229	65
Netherlands*	28549.7	79069.3	127.68	24.43	1.34	0.875	7689	99
Nicaragua	4452.8	8762.3	40.19	90.85	1.47	0.394	3195	90
Pakistan	4551.6	3793.2	30.24	85.09	1.47	0.343	1077	15
Panama	7897.9	19793.9	139.12	63.30	1.73	0.792	2423	73
Paraguay	6015.4	9689.0	67.70	87.77	1.58	0.549	1951	75
Peru	8386.6	18075.5	75.06	65.24	1.38	0.614	3310	61
Philippines	4472.8	8042.3	96.98	46.46	1.38	0.742	1668	72
Poland*†	8438.8	33948.8	98.10	19.50	1.12	0.849	—	—
Portugal*	12960.5	29436.8	59.47	63.82	1.49	0.581	2272	62
S. Korea*	13483.3	24650.9	159.26	28.46	1.53	0.895	1285	71
Singapore	21470.4	56218.5	89.34	71.33	1.71	0.682	2793	83
Sri Lanka	5476.3	5919.5	75.99	51.12	1.32	0.662	1794	75
Sweden*	27886.0	72777.3	132.60	28.28	1.31	0.860	7802	99
Switzerland*	30964.9	107869.8	142.18	22.21	1.37	0.898	10308	99
Taiwan†	15787.3	26240.0	96.91	35.82	1.27	0.775	—	—
Thailand	5557.7	7477.4	64.52	86.78	1.52	0.531	1308	68
Tunisia	7695.7	10823.4	35.73	82.32	1.38	0.375	1623	16
U.K.*	25775.3	50408.8	115.32	36.38	1.31	0.806	7634	99
U.S.A.*	35438.7	87330.1	228.61	6.33	1.48	0.982	12362	98
Uruguay	12036.3	23397.6	96.67	62.49	1.47	0.695	5119	94
Venezuela	17529.1	42713.1	70.71	69.46	1.40	0.588	10367	63
W. Germany*	28992.2	89368.2	93.70	41.19	1.22	0.735	7695	99

Notes: * OECD members. † Countries excluded from the Caselli-Coleman sample.

Table A2: Regressions for full sample (52 countries), OECD and non-OECD subsamples

Full Sample

Specification	Model 1	Model 2	Model 3	Model 4
Constant	0.47952***	0.44404***	−0.54935***	−0.66979***
	(0.05761)	(0.03897)	(0.19631)	(0.23007)
$\ln(w_1/w_2)$	−0.08304			0.08843
	(0.09936)			(0.08813)
$\ln(K/Y)$	0.30904***	0.31369***	0.16923***	0.16211***
	(0.05000)	(0.04965)	(0.04930)	(0.04994)
$\ln Y$			0.11844***	0.12830***
			(0.02310)	(0.02512)
s.e.e.	0.87538	0.89215	0.58183	0.57301
Adj. R^2	0.43	0.43	0.62	0.62
Obs.	52	52	52	52

OECD

Specification	Model 1	Model 2	Model 3	Model 4
Constant	0.68818***	0.73457***	−0.19106	−0.23115
	(0.22415)	(0.13233)	(0.62456)	(0.66551)
$\ln(w_1/w_2)$	0.07420			0.06873
	(0.28361)			(0.27161)
$\ln(K/Y)$	0.10461	0.07819	0.08148	0.10600
	(0.16989)	(0.13211)	(0.12613)	(0.16268)
$\ln Y$			0.09248	0.09219
			(0.06118)	(0.06329)
s.e.e.	0.19728	0.19822	0.16968	0.16874
Adj. R^2	0.02	0.02	0.12	0.12
Obs.	17	17	17	17

Non-OECD

Specification	Model 1	Model 2	Model 3	Model 4
Constant	0.45903***	0.45071***	−0.45256*	−0.59520*
	(0.05982)	(0.04029)	(0.26478)	(0.29747)
$\ln(w_1/w_2)$	−0.02343			0.11834
	(0.12297)			(0.11195)
$\ln(K/Y)$	0.25254***	0.24874***	0.17036***	0.14198**
	(0.06552)	(0.06160)	(0.05828)	(0.06399)
$\ln Y$			0.10675***	0.11868***
			(0.03107)	(0.03307)
s.e.e.	0.54775	00.54905	.40064	0.38718
Adj. R^2	0.31	0.31	0.49	0.49
Obs.	35	35	35	35

Notes: The dependent variable is skilled-labor share of the wage bill (S_1). w_1/w_2 is skilled-unskilled wage premium, K/Y is capital-output ratio and Y is output. Robust standard errors are given in parentheses. 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 A3: Model 1 vs. Specified Model

Specification	Test Statistic (p-value)
$\ln(w_1/w_2), \ln(K/Y), \ln Y$ [Model 4]	**15.84263** (0.00027)
$\ln(w_1/w_2), \ln(K/Y), [\ln(K/Y)]^2$	0.78134 (0.38176)
$\ln(w_1/w_2), \ln(K/Y), (\ln Y)^2$	**16.78205** (0.00019)
$\ln(w_1/w_2), \ln(K/Y), (\ln Y)^3$	**17.52808** (0.00014)
$\ln(w_1/w_2), \ln(K/Y), [\ln(K/Y)]^2, [\ln(K/Y)]^3$	0.40062 (0.67250)
$\ln(w_1/w_2), \ln(K/Y), [\ln(K/Y)]^2, (\ln Y)^3$	**8.69431** (0.00071)
$\ln(w_1/w_2), \ln(K/Y), \ln Y, [\ln(K/Y)]^2$	**8.10575** (0.00108)
$\ln(w_1/w_2), \ln(K/Y), \ln Y, (\ln Y)^2$	**8.95198** (0.00059)
$\ln(w_1/w_2), \ln(K/Y), \ln Y, (\ln Y)^3$	**8.99211** (0.00058)
$\ln(w_1/w_2), \ln(K/Y), \ln Y, [\ln(K/Y)]^2, (\ln Y)^2$	**5.82430** (0.00212)
$\ln(w_1/w_2), \ln(K/Y), \ln Y, [\ln(K/Y)]^2, [\ln(K/Y)]^3$	**5.52032** (0.00287)
$\ln(w_1/w_2), \ln(K/Y), \ln Y, (\ln Y)^2, [\ln(K/Y)]^3$	**5.84266** (0.00208)
$\ln(w_1/w_2), \ln(K/Y), \ln Y, [\ln(K/Y)]^2, (\ln Y)^3$	**5.84992** (0.00207)
$\ln(w_1/w_2), \ln(K/Y), \ln Y, (\ln Y)^2, (\ln Y)^3$	**6.07009** (0.00166)
$\ln(w_1/w_2), \ln(K/Y), [\ln(K/Y)]^2, [\ln(K/Y)]^3, (\ln Y)^3$	**5.90825** (0.00195)
$\ln(w_1/w_2), \ln(K/Y), \ln Y, [\ln(K/Y)]^2, (\ln Y)^2, [\ln(K/Y)]^3$	**4.42447** (0.00480)
$\ln(w_1/w_2), \ln(K/Y), \ln Y, [\ln(K/Y)]^2, (\ln Y)^2, (\ln Y)^3$	**4.44450** (0.04102)
$\ln(w_1/w_2), \ln(K/Y), \ln Y, [\ln(K/Y)]^2, [\ln(K/Y)]^3, (\ln Y)^3$	**4.45074** (0.00465)
$\ln(w_1/w_2), \ln(K/Y), \ln Y, (\ln Y)^2, [\ln(K/Y)]^3, (\ln Y)^3$	**4.46336** (0.00458)
$\ln(w_1/w_2), \ln(K/Y), \ln Y, [\ln(K/Y)]^2, (\ln Y)^2, [\ln(K/Y)]^3, (\ln Y)^3$	**3.80130** (0.01054)

Notes: The Null Hypothesis is that additional variables of Specified Model jointly equal to 0. The dependent variable is skilled-labor share of the wage bill (S_1). All of the specifications above were run with a constant. p-values are given in parentheses. Bold values indicate significance at the 5% level.

Table A4: Model 2 vs. Specified Model

Specification	Test Statistic (p-value)
$\ln(w_1/w_2), \ln(K/Y)$ [Model 1]	0.14429 (0.70593)
$\ln(K/Y), \ln Y$ [Model 3]	**12.73972** (0.00090)
$\ln(w_1/w_2), \ln(K/Y), \ln Y$ [Model 4]	**8.01836** (0.00112)
$\ln(w_1/w_2), \ln(K/Y), [\ln(K/Y)]^2$	0.46244 (0.63291)
$\ln(w_1/w_2), \ln(K/Y), (\ln Y)^2$	**8.48965** (0.00080)
$\ln(w_1/w_2), \ln(K/Y), (\ln Y)^3$	**8.86391** (0.00061)
$\ln(w_1/w_2), \ln(K/Y), [\ln(K/Y)]^2, [\ln(K/Y)]^3$	0.31384 (0.81526)
$\ln(w_1/w_2), \ln(K/Y), [\ln(K/Y)]^2, (\ln Y)^3$	**5.86152** (0.00199)
$\ln(w_1/w_2), \ln(K/Y), \ln Y, [\ln(K/Y)]^2$	**5.46786** (0.00296)
$\ln(w_1/w_2), \ln(K/Y), \ln Y, (\ln Y)^2$	**6.03387** (0.00168)
$\ln(w_1/w_2), \ln(K/Y), \ln Y, (\ln Y)^3$	**6.06071** (0.00163)
$\ln(w_1/w_2), \ln(K/Y), \ln Y, [\ln(K/Y)]^2, (\ln Y)^2$	**4.41644** (0.00474)
$\ln(w_1/w_2), \ln(K/Y), \ln Y, [\ln(K/Y)]^2, [\ln(K/Y)]^3$	**4.18769** (0.00632)
$\ln(w_1/w_2), \ln(K/Y), \ln Y, (\ln Y)^2, [\ln(K/Y)]^3$	**4.43025** (0.00465)
$\ln(w_1/w_2), \ln(K/Y), \ln Y, [\ln(K/Y)]^2, (\ln Y)^3$	**4.43572** (0.00463)
$\ln(w_1/w_2), \ln(K/Y), \ln Y, (\ln Y)^2, (\ln Y)^3$	**4.60140** (0.00376)
$\ln(w_1/w_2), \ln(K/Y), [\ln(K/Y)]^2, [\ln(K/Y)]^3, (\ln Y)^3$	**4.47961** (0.00438)
$\ln(w_1/w_2), \ln(K/Y), \ln Y, [\ln(K/Y)]^2, (\ln Y)^2, [\ln(K/Y)]^3$	**3.57762** (0.00929)
$\ln(w_1/w_2), \ln(K/Y), \ln Y, [\ln(K/Y)]^2, (\ln Y)^2, (\ln Y)^3$	**3.59370** (0.00908)
$\ln(w_1/w_2), \ln(K/Y), \ln Y, [\ln(K/Y)]^2, [\ln(K/Y)]^3, (\ln Y)^3$	**3.59871** (0.00901)
$\ln(w_1/w_2), \ln(K/Y), \ln Y, (\ln Y)^2, \ln(K/Y)^3, (\ln Y)^3$	**3.60884** (0.00888)

Notes: The Null Hypothesis is that additional variables of Specified Model jointly equal to 0. The dependent variable is skilled-labor share of the wage bill (S_1). All of the specifications above were run with a constant. p-values are given in parentheses. Bold values indicate significance at the 5% level.

Table A4: Model 2 vs. Specified Model (cont.)

Specification	Test Statistic (p-value)
$\ln(w_1/w_2), \ln(K/Y), \ln Y, [\ln(K/Y)]^2, (\ln Y)^2, [\ln(K/Y)]^3, (\ln Y)^3$	**3.19963** (0.01216)
$\ln(K/Y), [\ln(K/Y)]^2$	0.89467 (0.34950)
$\ln(K/Y), (\ln Y)^2$	**13.24819** (0.00073)
$\ln(K/Y), (\ln Y)^3$	**13.64323** (0.00062)
$\ln(K/Y), [\ln(K/Y)]^2, [\ln(K/Y)]^3$	0.45540 (0.63729)
$\ln(K/Y), [\ln(K/Y)]^2, (\ln Y)^3$	**6.72404** (0.00292)
$\ln(K/Y), \ln Y, [\ln(K/Y)]^2$	**6.40872** (0.00372)
$\ln(K/Y), \ln Y, (\ln Y)^2$	**6.85644** (0.00265)
$\ln(K/Y), \ln Y, (\ln Y)^3$	**6.88318** (0.00260)
$\ln(K/Y), \ln Y, [\ln(K/Y)]^2, (\ln Y)^2$	**4.46233** (0.00840)
$\ln(K/Y), \ln Y, [\ln(K/Y)]^2, [\ln(K/Y)]^3$	**4.35192** (0.00945)
$\ln(K/Y), \ln Y, (\ln Y)^2, [\ln(K/Y)]^3$	**4.48219** (0.00823)
$\ln(K/Y), \ln Y, [\ln(K/Y)]^2, (\ln Y)^3$	**4.47959** (0.00825)
$\ln(K/Y), \ln Y, [\ln(K/Y)]^2, [\ln(K/Y)]^3$	**4.35192** (0.00945)
$\ln(K/Y), \ln Y, (\ln Y)^2, [\ln(K/Y)]^3$	**4.48219** (0.00823)
$\ln(K/Y), \ln Y, [\ln(K/Y)]^2, (\ln Y)^3$	**4.47959** (0.00825)
$\ln(K/Y), \ln Y, (\ln Y)^2, (\ln Y)^3$	**4.68011** (0.00668)
$\ln(K/Y), [\ln(K/Y)]^2, [\ln(K/Y)]^3, (\ln Y)^3$	**4.55642** (0.00761)
$\ln(K/Y), \ln Y, [\ln(K/Y)]^2, (\ln Y)^2, (\ln Y)^3$	**3.42679** (0.01683)
$\ln(K/Y), \ln Y, [\ln(K/Y)]^2, (\ln Y)^2, [\ln(K/Y)]^3$	**3.38401** (0.01780)
$\ln(K/Y), \ln Y, [\ln(K/Y)]^2, [\ln(K/Y)]^3, (\ln Y)^3$	**3.40098** (0.01741)
$\ln(K/Y), \ln Y, (\ln Y)^2, [\ln(K/Y)]^3, (\ln Y)^3$	**3.44825** (0.01637)
$\ln(K/Y), \ln Y, [\ln(K/Y)]^2, (\ln Y)^2, [\ln(K/Y)]^3, (\ln Y)^3$	**2.92875** (0.02441)

Notes: The Null Hypothesis is that additional variables of Specified Model jointly equal to 0. The dependent variable is skilled-labor share of the wage bill (S_1). All of the specifications above were run with a constant. p-values are given in parentheses. Bold values indicate significance at the 5% level.

Table A5: Model 4 vs. Specified Model

Specification	Test Statistic (p-value)
$\ln(w_1/w_2), \ln(K/Y), \ln Y, [\ln(K/Y)]^2$	0.54173 (0.81831)
$\ln(w_1/w_2), \ln(K/Y), \ln Y, (\ln Y)^2$	1.77067 (0.54336)
$\ln(w_1/w_2), \ln(K/Y), \ln Y, (\ln Y)^3$	1.82891 (0.53615)
$\ln(w_1/w_2), \ln(K/Y), \ln Y, [\ln(K/Y)]^2, (\ln Y)^2$	0.86577 (0.67467)
$\ln(w_1/w_2), \ln(K/Y), \ln Y, [\ln(K/Y)]^2, [\ln(K/Y)]^3$	0.53469 (0.83269)
$\ln(w_1/w_2), \ln(K/Y), \ln Y, (\ln Y)^2, [\ln(K/Y)]^3$	0.88576 (0.66655)
$\ln(w_1/w_2), \ln(K/Y), \ln Y, [\ln(K/Y)]^2, (\ln Y)^3$	0.89367 (0.66338)
$\ln(w_1/w_2), \ln(K/Y), \ln Y, (\ln Y)^2, (\ln Y)^3$	1.13347 (0.57825)
$\ln(w_1/w_2), \ln(K/Y), \ln Y, [\ln(K/Y)]^2, (\ln Y)^2, [\ln(K/Y)]^3$	0.72292 (0.73779)
$\ln(w_1/w_2), \ln(K/Y), \ln Y, [\ln(K/Y)]^2, (\ln Y)^2, (\ln Y)^3$	0.74232 (0.72684)
$\ln(w_1/w_2), \ln(K/Y), \ln Y, [\ln(K/Y)]^2, [\ln(K/Y)]^3, (\ln Y)^3$	0.74836 (0.72345)
$\ln(w_1/w_2), \ln(K/Y), \ln Y, (\ln Y)^2, [\ln(K/Y)]^3, (\ln Y)^3$	0.76058 (0.71666)
$\ln(w_1/w_2), \ln(K/Y), \ln Y, [\ln(K/Y)]^2, (\ln Y)^2, [\ln(K/Y)]^3, (\ln Y)^3$	0.84822 (0.66446)

Notes: The Null Hypothesis is that additional variables of Specified Model jointly equal to 0. The dependent variable is skilled-labor share of the wage bill (S_1). All of the specifications above were run with a constant. p-values are given in parentheses. Bold values indicate significance at the 5% level.