# A Nonparametric Examination of Capital-Skill Complementarity

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**Abstract**

This paper uses nonparametric kernel methods to construct observation specific elasticities of substitution for a panel of 73 developed and developing countries to examine the capital-skill complementarity hypothesis. The exercise shows weak support for capital-skill complementarity. That being said, the added flexibility of the nonparametric procedure is able to uncover that the elasticities of substitution vary across countries, groups of countries and time periods.

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# 1 Introduction

Rising wage inequality has been a key feature of the U.S. labor market since the late 1970s. This phenomenon, both in the United States and worldwide, has received much attention in the literature. One possible explanation given for this rise comes from the capital-skill complementarity (CSC) hypothesis. The hypothesis states that physical capital and skilled labor are more complementary than unskilled labor and physical capital. Assuming the hypothesis is true, an increase in physical capital, *ceteris paribus*, will increase the demand for skilled labor (and thus wages for skilled laborers). Capital-deepening seen across many economies in recent years combined with CSC could be one such explanation for rising wage inequality. Thus, if significant increases in physical capital have been made and CSC is shown to hold for a particular economy, policymakers could use this information to possibly find ways to decrease inequality.

Griliches (1969) finds empirical evidence that physical capital and skilled labor are less substitutable than physical capital and unskilled labor and concludes that the CSC hypothesis holds using a data set of U.S. manufacturers. Since Griliches (1969), the CSC hypothesis has been empirically studied in great detail. While some authors argue on the specification of the model, others argue on the type of data which should be studied. Fallon and Layard (1975), and others, study the CSC hypothesis on an international scale. Specifically, they piece together data from 22 developed and developing countries for the year 1963. They find mild evidence in favor of the CSC hypothesis. Duffy, Papageorgiou, and Perez-Sebastian (2004), hereafter DPP, extend the work of Fallon and Layard (1975) to a data set of 73 countries over a 25 year period (1965-1990). They use a two-level constant elasticity of substitution production function specification and use nonlinear estimation methods which allow them to relax the assumption of perfectly competitive markets. Further, they are able to categorize skilled (and thus unskilled) labor into five categories (or thresholds)[1] which allow them to find the greatest support for CSC when the threshold for skilled laborers is defined as those who have attained some secondary education, those who have completed primary education or as those who gained some primary education.

[1] These thresholds will be described in greater detail in Section 3.

Part of their purpose for looking at an international panel was to find evidence of CSC over long periods of time and across countries at different stages of development. This strategy was partly influenced by Goldin and Katz (1998) who note that physical capital and skilled labor have not always been viewed as relative complements. In particular, they suggest that transitions between production processes change the relative demand for skill, thus different economies at different times may or may not possess CSC.

Therefore it seems desirable to view the elasticities of substitution for each country at each time period. Simply blanketing all countries under one estimate could prove to be detrimental. For example, suppose a researcher found that CSC exists in a panel of countries. Then if countries take that information as given, it may affect their policy. If CSC holds true for that economy, it could increase spending on education to potentially reduce the impact of advancing technology on inequality. However, if CSC does not exist, those resources spent on education may have been better allocated.

Although observation specific estimates seem logical, the aforementioned papers simply give a single estimate for each elasticity.[2] In general, an increasingly popular method to obtain observation specific estimates is to use nonparametric kernel methods. In addition to obtaining observation specific estimates, nonparametric methods have the luxury of not having to assume a specific functional form for the technology. This technique is extremely beneficial here because as DPP (pp. 331) note, "there is no consensus yet on the appropriate functional form to use to capture capital-skill complementarity." Thus, if one chooses a specific technology, and that assumption is incorrect, estimation will most likely lead to biased estimates.

This paper will use nonparametric methods to study the CSC hypothesis. This approach allows for at least three contributions to the literature. (1) The nonparametric technique allows the model to be solved using a single-level production function. (2) It decreases the number of assumptions of the model, including the choice of functional form for the technology and (3) it allows for observation specific estimates of elasticities of substitution. These contributions allow for estimates of elasticities

[2] There is, however, some work being done with translog cost functions (which require price data) that allow for observation specific estimates, e.g. see Bergström and Panas (1992) and Ruiz-Arranz (2002).

of substitution which sidestep the problem of specification choice which arises in the two-level production function approach. Further, no assumptions on the parametric form of the technology will have to be assumed, nor will it require additional restrictive assumptions such as assuming neutral technological growth.

The main finding of the paper shows weak support for the CSC hypothesis. As in DPP, the elasticities of substiution between physical capital and skilled labor are generally smaller than the elasticities of substitution between physical capital and unskilled labor, but the difference is often insignificant. Also, as hypothesized by Goldin and Katz (1998), it is shown that the degree of substitutability varies amongst countries, across groups of countries and across time.

The remainder of the paper is organized as follows: Section 2 describes the model, gives a brief history of elasticity of substitution measures, and describes the estimation procedure as well as a nonparametric testing procedure. The third section gives the data while the fourth describes the results. Finally, the fifth section concludes.

# 2 Methodology

## 2.1 Model

Consider the simple aggregate production model of the form

$$y = f(K, S, N), \tag{1}$$

where the function $f$ transforms inputs into aggregate output ($y$). $K$ represents physical capital stock, and $S$ and $N$ represent skilled and unskilled labor, respectively. The CSC hypothesis states that capital and skilled labor are more complementary than capital and unskilled labor. Formally, denoting $\sigma_{ql}$ as the elasticity of substitution between inputs $q$ and $l$, CSC is said to hold if $\sigma_{KS} < \sigma_{KN}$. That is, $K$ and $S$ are less substitutable (or more complementary) than $K$ and $N$.

## 2.2 Elasticity of Substitution Measures

The elasticity of substitution measure, first developed by Hicks (1932), measures the percentage change in factor proportions due to a change in the marginal rate of technical substitution in a two-input world. It is, effectively, a measure of the curvature of an isoquant. Although this result is intuitive, complication occurs when one allows for more than two inputs. Several measures have since been created in order to combat this complication. Unfortunately, there is no one correct answer.

One such measure, which has fallen out of fashion in the literature, is the direct elasticity of substitution (DES) defined by Allen and Hicks (1934). The measure, which defines the elasticity of substitution between any two inputs as

$$\sigma_{ql}^{D} = \frac{x_q f_q + x_l f_l}{x_q x_l} \frac{H_{ql}}{|H|}, \tag{2}$$

where

$$H = \begin{bmatrix} 0 & f_1 & \cdots & f_P \\ f_1 & f_{11} & \cdots & f_{1P} \\ \vdots & & & \vdots \\ f_P & f_{P1} & \cdots & f_{PP} \end{bmatrix},$$

$H_{ql}$ is the cofactor of the element $f_{ql}$ in $H$, and $f_q$, $f_{qq}$, and $f_{ql}$ represent the first partial, second partial, and cross-partial derivatives of the production function respectively, can be interpreted as $\partial \log (x_q/x_l) / \partial \log (f_l/f_q)$ for constant output and other input quantities. The downfall of this measure is that it is identical to the two-input case, effectively assuming that the other factors in the production function are fixed and can be ignored. It is only theoretically plausible to use an aggregate production like this if in fact all factors are being competitively allocated. If one factor is being held constant, then an aggregate production function no longer exists.

The most popular measure in the literature is the Allen-Uzawa (or the partial) elasticity of substitution (AES). This method, first suggested by Allen and Hicks (1934) and further studied by Allen (1938) and Uzawa (1962), has become a staple in the applied literature. It was designed to combat the downfall of the DES measure (by attempting to examine changes in other inputs) and is formally defined as

$$\sigma_{ql}^{A} = \frac{\sum_p x_p f_p}{x_q x_l} \frac{H_{ql}}{|H|}. \tag{3}$$

Although the measure is continually used, it has met sharp criticism. Blackorby and Russell (1989) show that the Allen-Uzawa measure fails to preserve the relevant properties of the original Hicksian notion (for the multi-input case). They further state (pp. 883) that “as a quantitative measure, it has no meaning; as a qualitative measure, it adds no information to that contained in the (constant output) cross-price elasticity. In short, the AES is (incrementally) completely uninformative." Perhaps the only redeaming feature of the AES is that it preserves the sign of the compensated derivative.

In its place they suggest an alternative elasticity of subsitution measure originally published in Japanese by Morishima (1967) and independently discovered by Blackorby and Russell (1975, 1981). This measure, which Klump and de La Grandville (2000) term[3] the Morishima-Blackorby-Russell elasticity of substitution (MES), preserves the salient characteristics of the original Hicksian concept, which are lacking in the Allen-Uzawa measure. This measure is usually employed when estimating cost functions (e.g., see Thompson and Taylor 1995), but is also used when estimating production functions (e.g., see Hoff 2004) and has a well-known relationship to the partial elasticity of substitution:

$$\begin{aligned} \sigma_{ql}^{M} &= \frac{f_l}{x_q}\frac{H_{ql}}{|H|} - \frac{f_l}{x_l}\frac{H_{ql}}{|H|} \\ &= \frac{f_l x_l}{f_q x_q}\left(\sigma_{ql}^{A} - \sigma_{ll}^{A}\right). \end{aligned} \tag{4}$$

A detailed examination of this formula shows two important facts. First, a pair of goods can be complements in terms of the AES, but substitutes according to the MES. On the other hand, if two goods are substitutes according to the AES, they are always substitutes according to the MES. Thus, either the MES has a bias towards treating inputs as substitutes or the AES has a bias towards treating them as complements. However, this paradoxical result should not be too disturbing since it simply reflects the fluidity of the concept of the elasticity of substitution in a multi-input world. Second, the MES is asymmetric. Although some view this as an unusual property, Blackorby and Russell (1981, 1989) argue that this should be natural for the multi-input case.[4]

[3] This under-cited paper not only suggests the name for the elasticity of substitution measure, it also proposes that empirical growth research in this area be based on the MES.

[4] When examining the asymmetric property for this data set, it is found that, in general, the absolute value of $\sigma_{KS}$ is less than $\sigma_{SK}$ and at the same time $\sigma_{KN}$ is less than $\sigma_{NK}$. What these inequalities (literally) say is that the capital-labor ratio (skilled or unskilled) is more sensitive to changes in the rental rate on capital than to changes in the wage rate (which change the factor price ratio in different directions). Given that the main conclusions of the paper do not change with either measure, to conserve space, the paper chooses to focus on the estimates of $\sigma_{KS}$ and $\sigma_{KN}$. The results using $\sigma_{SK}$ and $\sigma_{NK}$ are available in Appendix A. For a more detailed discussion on

## 2.3 Nonparametric Estimation of Production Functions

Nonparametric estimation of production functions is not new, but the literature is somewhat scattered. Early attempts to estimate production functions using kernel methods can be found in, for example, Vinod and Ullah (1988) and Kneip and Simar (1996). The term nonparametric estimation encompasses a broad range of methods for which to estimate production functions and includes other approaches such as Allon et al. (2005) who use entropy measures, Chavas and Cox (1988) who use Data Envelopment Analysis, Epple et al. (2006, 2007) who use series estimation, Kumbhakar et al. (2007) who use local-maximum likelihood estimation and Lewbel and Linton (2007) who use nonparametric matching estimators.

The choice of which methodology to choose depends on the problem at hand and the data in question. This paper uses Li-Racine Generalized Kernel Estimation (see Li and Racine 2004, and Racine and Li 2004). This methodology is not new to the estimation of production functions either. For example, Henderson and Kumbhakar (2006) use generalized kernel estimation to estimate the U.S. aggregate production function and examine the public capital productivity puzzle. The benefit of this procedure is that it smooths both continuous and categorical regressors. Besides the obvious benefit of being able to smooth categorical variables, and not having to automatically resort to a semiparametric procedure, the rate of convergence of the estimators depend only on the number of continuous regressors. This is especially important because the data set being studied is relatively small.

### 2.3.1 Generalized Kernel Estimation

Here, generalized kernel estimation is used to estimate the (single level) production function (1), which may be written as

$$y_i = m(x_i) + u_i, \qquad i = 1, 2, ..., NT. \tag{5}$$

$m$ is the unknown smooth production function with argument $x_i = (x_i^c, x_i^u, x_i^o)$, $x_i^c = (K_i, S_i, N_i)$ is a vector of continuous inputs, $x_i^u$ is a vector of regressors that assume

elasticity of substitution measures, see e.g., Allen (1938), Allen and Hicks (1934), Blackorby and Russell (1975, 1981, 1989), Chambers (1988), Hicks (1932, 1946), and McFadden (1963).

unordered discrete values (in this case a single variable for geographic region[5]), $x_i^o$ is a vector of regressors that assume ordered discrete values (in this case a single variable for time), $u$ is the additive error, $N$ is the number of countries, and $T$ is the number of time periods ($N = 73$, $T = 6$). Taking a second-order Taylor expansion of (5) with respect to $x_j$ yields

$$y_i \approx m(x_j) + (x_i^c - x_j^c)\beta(x_j) + 0.5(x_i^c - x_j^c)'(x_i^c - x_j^c)\gamma(x_j) + u_i, \tag{6}$$

where $\beta(x)$ ($\equiv \bigtriangledown m(x)$) is the partial derivative of $m(x)$ with respect to $x^c$ and $\gamma(x)$ ($\equiv \bigtriangledown_2 m(x)$) is the Hessian.

The local-quadratic least-squares[6] estimator of $\delta(x) \equiv (m(x), \beta(x), \gamma(x))'$ is given by

$$\widehat{\delta}(x) = \left(\widehat{m}(x), \widehat{\beta}(x), \widehat{\gamma}(x)\right)' = \left(X'K(x)K\right)^{-1} X'K(x)y, \tag{7}$$

where $X = \left(1, (x_i^c - x_j^c), (x_i^c - x_j^c)'(x_i^c - x_j^c)\right)$ and $K(x)$ is a $NT \times NT$ diagonal matrix of kernel (weight) functions commonly used for mixed data (Li and Racine 2006).[7]

### 2.3.2 Bandwidth Selection

Estimation of the bandwidths is typically the most salient factor when performing nonparametric estimation. Although there exist many selection methods, this study utilizes Hurvich et al.'s (1998) Expected Kullback Leibler ($AIC_c$) criteria. This method – which chooses smoothing parameters using an improved version of a criterion based on the Akaike Information Criteria – has been shown to perform well in small samples and avoids the tendency to undersmooth as often happens under other

[5]Maasoumi, Racine and Stengos (2007) use generalized kernel estimation in their study of a nonparametric growth regression, but choose to only include OECD status. Following the lead of Temple (1998), in addition to OECD status, the regional categorical variable includes categories for Africa, the Caribbean, Latin American, the Middle East, and Asia. The results of the exercise were also examined solely using OECD status and although these coefficients have more variation, the main conclusions of the paper do not change. The results are available upon request.

[6]It should be noted that the second-order Taylor expansion and thus estimation of the model by local-quadratic least-squares is not necessary here. For instance, estimation of (5) can be performed using local-constant least-squares (which estimates only the unknown function) and then separately obtaining the derivatives of $m(\cdot)$ (using methods outlined in, e.g. Pagan and Ullah 1999, Rilstone and Ullah 1989, Ullah 1988a,b, and Vinod and Ullah 1988). For further information on the benefits and relationships between local constant, linear and quadratic least-squares, see Fan and Gijbels (1996).

[7]See Hall, Li and Racine (2007), Hall, Racine and Li (2004), Li and Racine (2004, 2006) and Racine and Li (2004) for further details.

approaches such as Least-Squares Cross-Validation. Specifically, the bandwidths are chosen to minimize

$$AIC_c = \log\left(\widehat{\sigma}^2\right) + \frac{1 + \text{tr}(H)/N}{1 - \left[\text{tr}(H) + 2\right]/N} \tag{8}$$

where

$$\begin{aligned}\widehat{\sigma}^2 &= \frac{1}{N}\sum_{j=1}^{N}\left(y_j - \widehat{m}(x_j)\right)^2 \\ &= \left(\frac{1}{N}\right) y'(I-H)'(I-H)y,\end{aligned} \tag{9}$$

and $\widehat{m}(x_j) = Hy_j$.

A major benefit of nonparametric type estimators is that they give a separate estimate for each observation. This allows one to construct observation specific estimates of (2), (3), and (4), where observation specific values of $f_q = \frac{\partial m}{\partial x_q}$, $f_{qq} = \frac{\partial^2 m}{\partial x_q^2}$, and $f_{ql} = \frac{\partial^2 m}{\partial x_q \partial x_l}$ are retrieved from $\widehat{\beta}(x)$ and $\widehat{\gamma}(x)$. This result allows one to track elasticity of substitution estimates across countries and over time.

In addition to giving observation specific estimates and relaxing the functional form,[8] the nonparametric model gives several other important benefits over the parametric models. First, the model does not require the elasticity of substitution between $N$ and $S$ to be the same as that between $K$ and $N$ (equation 1 in DPP) or $K$ and $S$ (equation 2 in DPP).[9] Second, the model does not require Hicks-neutral technological growth (equations 5 and 6 in DPP). Finally, it allows for time effects which are allowed to vary across countries (embodied technical change).

[8] It should also be noted here that the translog model allows for observation specific estimates and a partial relaxation of the functional form. However, there are a few downfalls to the second-order taylor approximation of the constant elasticity of substitution production function. First, as compared to the nonparametric model, it is more restrictive. Second, some authors have found that the second-order taylor expansion sometimes gives poor results (see Kmenta 1967, and Thursby and Lovell 1978 for further details). Results for this paper were also estimated using the translog production function. It was found that these results were less intuitive than the nonparametric model, but are available from the author upon request.

[9] In the estimation of the model it is found that the elasticities of substitution between $N$ and $S$, and $K$ and $N$ or $K$ and $S$ are not equal. The results for elasticities of subsitution between $N$ and $S$ are not reported in the tables, but are available from the author upon request.

### 2.3.3 Identification

In theory, the relationship between capital-skill complementarity and the distribution of income relies on a number of assumptions. Some of them are general to much of the production theory literature such as returns to scale. Some are special to the capital-skill complementarity literature. With nonparametric estimation it is not entirely clear to what extent the elasticities obtained are able to confirm or refute theoretical predictions.

Perhaps more important than refuting/confirming theories is the issue of identification. Diamond et al. (1978) show for what conditions the elasticities of substitution and patterns of technological change can be identified and for what conditions they cannot be identified. For example, the Cobb-Douglas production function implicitly assumes that the elasticity of subsitution between inputs is equal to zero. Hence, nonparametric identification is not guaranteed because the nonparametric model nests the Cobb-Douglas model. In that sense, the nonparametric model is not fully identified.

This stems the question, what should one do from here? One tedious approach would be to reject any parametric model for which the desired estimates are not identified. For example, using the Hsiao, Li and Racine (2007) test, the Cobb-Douglas model is rejected at the 1% level for each data set run in this paper. However, this approach, of course, is infeasible in practice. A likely better solution would be to develop tests for the conditions outlined in Diamond et al. (1978). If it is found that the conditions do not hold, then procedures may be developed to estimate the nonparametric model imposing these assumptions (for example, neutral technological change). There is a small literature on testing for structure (e.g., see Bowman, Jones and Gijbels, 1998 and Hall and Van Keilgom, 2005) and imposing strucutre in nonparametric kernel estimators (e.g., see Hall and Huang, 2001 and Hall, Huang, Gifford and Gijbels, 2002). This possibility suggests a non-trivial future research agenda

## 2.4 Stochastic Dominance

Nonparametric estimation as described in equation (7) allows one to generate unique elasticity of substitution estimates for each observation. To examine the empirical comparisons, this paper uses a stochastic dominance (SD) approach. The comparison of the elasticities of substitution between physical capital, and skilled and unskilled labor on a particular index is highly subjective; different indices may yield different substantive conclusions. In contrast, finding a SD relation provides uniform ranking regarding the elasticities of substitution and offers robust inference.

To proceed, let $\sigma_{KN_i}$ be the actual elasticity of substitution between physical capital and unskilled labor unique to an individual country during a specific year. $\sigma_{KS_i}$ is defined similarly. In practice, the actual elasticities of substitution are unknown, but the nonparametric regression allows us to construct an estimate of each of these. Define $\{\widehat{\sigma}_{KN}\}_{i=1}^{NT}$ as a vector of $NT$ estimates of $\sigma_{KN}$ and $\{\widehat{\sigma}_{KS}\}_{i=1}^{NT}$ as an analogous vector of estimates of $\sigma_{KS}$. Let $G(\sigma_{KN})$ and $F(\sigma_{KS})$ represent the cumulative distribution functions of $\sigma_{KN}$ and $\sigma_{KS}$, respectively.

Consider the null hypotheses of interest as
*Equality of Distributions* :

$$G(\sigma_{KN}) = F(\sigma_{KS}) \quad \forall \sigma_{KN} \cup \sigma_{KS} \in \Omega. \tag{10a}$$

*First Order Stochastic Dominance* : $G$ dominates $F$ (CSC) if

$$G(\sigma_{KN}) \leq F(\sigma_{KS}) \quad \forall \sigma_{KN} \cup \sigma_{KS} \in \Omega, \tag{10b}$$

where $\Omega$ is the union support for $\sigma_{KN}$ and $\sigma_{KS}$. To test this null hypotheses, define the empirical cumulative distribution function for $\sigma_{KN}$ as

$$\widehat{G}(\sigma_{KN}) = \frac{1}{NT} \sum_{i=1}^{NT} 1(\widehat{\sigma}_{KN} \leq \sigma_{KN}), \tag{11}$$

where $1(\cdot)$ denotes the indicator function and $\widehat{F}(\sigma_{KS})$ is defined similarly. Next, define the following Kolmogorov-Smirnov statistics

$$T_{EQ} = \sup_{\sigma_{KN} \cup \sigma_{KS} \in \Omega} |\widehat{G}(\sigma_{KN}) - \widehat{F}(\sigma_{KS})|; \tag{12a}$$

$$T_{FSD} = \sup_{\sigma_{KN} \cup \sigma_{KS} \in \Omega} \left\{ \widehat{G}(\sigma_{KN}) - \widehat{F}(\sigma_{KS}) \right\}; \tag{12b}$$

for testing the equality and first order stochastic dominance (FSD) relation, respectively.

Unfortunately, the asymptotic distributions of these nonparametric sample based statistics under the null are generally unknown because they depend on the underlying distributions of the data. Thus one needs to approximate the empirical distributions of these test statistics to overcome this problem. The strategy following Abadie (2002) is as follows:

(i) Let $T$ be a generic notation for $T_{EQ}$ and for $T_{FSD}$. Compute the test statistics $T$ for the original sample of $\{\widehat{\sigma}_{KN_1}, \widehat{\sigma}_{KN_2}, \ldots, \widehat{\sigma}_{KN_{NT}}\}$ and $\{\widehat{\sigma}_{KS_1}, \widehat{\sigma}_{KS_2}, \ldots, \widehat{\sigma}_{KS_{NT}}\}$.

(ii) Define the pooled sample as $\Omega = \{\widehat{\sigma}_{KN_1}, \widehat{\sigma}_{KN_2}, \ldots, \widehat{\sigma}_{KN_{NT}}, \widehat{\sigma}_{KS_1}, \widehat{\sigma}_{KS_2}, \ldots, \widehat{\sigma}_{KS_{NT}}\}$. Resample $NT + NT$ observations with replacement from $\Omega$ and call it $\Omega_b$. Divide $\Omega_b$ into two groups to obtain $\widehat{T}_b$.

(iii) Repeat step (ii) $B$ times.

(iv) Calculate the p-values of the tests with p-value $= B^{-1} \sum_{b=1}^{B} 1(\widehat{T}_b > T)$. Reject the null hypotheses if the p-value is smaller than some significance level $\alpha$, where $\alpha \in (0, 1/2)$.

By resampling from $\Omega$, we approximate the distribution of the test statistics when $G(\sigma_{KN}) = F(\sigma_{KS})$. Note that for (12b), $G(\sigma_{KN}) = F(\sigma_{KS})$ represents the least favorable case for the null hypothesis. This strategy allows us to estimate the supremum of the probability of rejection under the composite null hypothesis, which is the conventional definition of test size.[10]

# 3 Data

The data used in this paper is identical to that of DPP and will only be briefly described here. Real GDP ($y$) and physical capital stock ($K$), which are both measured in constant U.S. dollars (1985 international prices), as well as skilled labor ($S$) and

[10] Ideally one would like to reestimate the nonparametric returns within each bootstrap replication to take into account the uncertainty of the returns. Unfortunately, it could be argued that in doing this one should reestimate the bandwidths for each bootstrap replication, which would be extremely computationally difficult, if not impossible. Thus, the bootstrapped p-values most likely differ slightly from their "true" values. Nonetheless, if one obtains a large p-value, it is unlikely that accounting for such uncertainty would alter the inference. That being said, determining an ideal bootstrapping procedure is a promising area for future research.

unskilled labor ($N$) were obtained from the Penn World Tables Mark 5.6. There are six annual observations for each of the 73 countries (both developed and developing), spaced 5 years apart, over the period 1965-1990. Five proxies are constructed for skilled and unskilled labor (because it is unclear how skilled labor should be defined in a cross-country analysis) based on the Barro and Lee (2001) international education data set (observations are available once every five years). Specifically, DPP obtain each of the skilled proxies by multiplying achievement rates for a particular cutoff criterion by the size of the labor force in each country at each point in time (within the sample). Specifically, the proxies for skilled labor are as follows: ($S1$) workers who have attained some college, ($S2$) workers who have completed secondary education, ($S3$) workers who have attained some secondary education, ($S4$) workers who have completed primary education, and ($S5$) workers who have attained some primary education. The remaining portion of the labor force in each category is considered unskilled labor, and is correspondingly labeled as $N1$, $N2$, $N3$, $N4$, and $N5$.[11]

# 4 Results

The results of this study are displayed in Tables 1-4. Table 1 gives the SD tests for the equality of distributions, as well as tests for FSD. Table 2 presents the elasticities of substitution between physical capital, and skilled and unskilled labor. The table reports the elasticity of substitution at the 25th, 50th and 75th percentile (labelled Quartile 1, 2 and 3) along with the corresponding standard error below each estimate in italics. Table 3 presents the median results for specific groups of countries across the sample and Table 4 gives the median elasticities for each time period. For the sake of comparison, the first table gives the results for each elasticity of substiitution measure. For the sake of brevity, as well as following the suggestion of Klump and de La Grandville (2000), the final three tables give the results for only the MES.[12]

[11] It should be obvious that $S1 \leq S2 \leq S3 \leq S4 \leq S5$ and that $N1 \geq N2 \geq N3 \geq N4 \geq N5$

[12] The results of the three tables for the other elasticity of substitution measures are available in Appendix B..

## 4.1 Stochastic Dominance Tests

To test the differences between the estimated distributions of parameter estimates, SD tests are employed. Here two separate null hypotheses are tested First, the null that the distribution (for all countries over all time periods) of the estimated elasticity of substitution between physical capital and skilled labor (at a given threshold) is different from the distribution of the estimated elasticity of substitution between physical capital an unskilled labor (at the same threshold) is tested. Once it has been determined that the distributions are different from one another, the test for the null that $\sigma_{KN}$ first order dominates $\sigma_{KS}$ can be performed. This test will provide statistical evidence of whether or not there exists a first order dominance relation, and hence, whether or not there exists general evidence of CSC across the entire sample.

If a dominance relation for $\sigma_{KN}$ over $\sigma_{KS}$ is found, one has discovered significant evidence supporting the hypothesis that the elasiticity of substitution between physical capital and unskilled labor is larger than that of physical capital and skilled labor for the entire sample (over all countries and time periods). Further, if dominance is not found, one has discovered an equally interesting result. Lack of dominance relations means that the empirical cumulative distributions cross, and that, in turn, means that one cannot find significant evidence of CSC across the entire sample.

The results of the tests are reported in Table 1. In each circumstance, the tests reject the null that the two distributions are equal at conventional confidence levels. In terms of rankings, these results differ across thresholds and across elasticity of substitution measures. Depending on the elasticity of substitution choice, there is some significant evidence of CSC at each threshold. In the fifteen (five thresholds $\times$ three measures) cases considered, failure to reject the null of CSC (p-values in excess of 0.500) is concluded in seven of them.[13]

Although at each threshold there is some evidence of CSC, the results for significance differ according to the elasticity of substitution measure. For the DES measure, there appears to be strong evidence of CSC for the lower two thresholds and no evidence for the higher three thresholds. The AES only shows significant evidence of

[13]Here the upper bound of 0.500 is chosen as the critical point for testing the null hypotheses given the sample size and concerns of uncertainty in the elasticities.

CSC for the second and third thresholds and the MES measure only shows significant evidence for the highest three thresholds.

In sum, employing SD tests on the elasticity of substitution estimates reveals at least two findings. First, SD tests find some support for CSC in each of the thresholds. Second, the SD tests revealed that there are cases where the cummulative distributions cross and thus no uniform evidence of CSC across the sample.

## 4.2 Comparison of Quartiles

Given that we do not find FSD at each threshold for a given measure, it may prove fruitful to examine the quartiles of the elasticity of substitution estimates. Table 2 gives the individual elasticity of substitution estimates at their quartiles for each of the proxy levels (thresholds). When using nonlinear least squares (with or without fixed effects) DPP find general evidence for CSC. Further, they find stronger evidence when skilled labor is defined as those who have attained some secondary education, completed primary education or attained some primary education and insignificant evidence when skilled labor is defined as workers who have attained some college or workers who have completed secondary education. However, when using a GMM-IV estimator, their evidence for CSC is greatly weakened.

The former method is comparable to the nonparametric approach in this paper. Table 2 shows that for each threshold, the results show an overwhelming majority (14 of the 15) of the quartiles show evidence of CSC. Unfortunately, a majority of this evidence is insignificant. In fact of those 14 quartiles that show evidence of CSC, only three of them show significant evidence of CSC. This finding can be consistent with at least two stories. First, it may be an artifact of the small sample. Second, it may be difficult to obtain a significant result because, as Goldin and Katz (1998) argue, CSC is subject to change and may or may not hold for different countries in different time periods.

If the study were to stop here, it would conclude with DPP (pp. 340) that "there is some evidence in support of the capital-skill complementarity hypothesis at the aggregate production level, but the evidence is not very strong." Fortunately, the nonparametric approach allows for observation specific estimates and thus the estimates can be further broken down to examine different strata.

## 4.3 Comparison by Group

Although results at the quartiles are informative, one can always wonder how groups of countries behave together. Table 3 reports the median elasticity of substitution for specific groups of countries.[14] The table shows CSC for most groups at most thresholds. A few points are worth noting. First, for each of the groups, CSC generally holds for the median values. This should not necessarily be surprising. These results are consistent with those in the second quartile of Table 2. Second, the median elasticity of substitution between physical capital and skilled labor for the OECD countries is generally less than that of the non-OECD countries, but greater than that of the Latin American countries. Second, the elasticity of substiution between physical capital and unskilled labor is the smallest for OECD countries, regardless of the threshold. However, more important is the prevelance of CSC across groups. Here it is seen that CSC is more prounounced in non-OECD economies as opposed to OECD economies. The same holds true for Latin American countries as compared to OECD countries.

These result are not necessarily surprising. In a recent paper, Papageorgiou and Chemlarova (2005) find that a particular group of countries ("Regime 2" in Table 3 of their paper), who have a moderate income level but a low level of education, have a more pronounced level of CSC compared with countries with a high education ("Regime 1") or countries with both a low income and low education level ("Regime 3"). In this sample it is found that their results hold. CSC is more pronounced in Regime 2 relative to Regime 3, and at the same time it is more prounced for Regime 2 relative to Regime 1. However, it must be noted that this data set is not identical to Papageorgiou and Chemlarova (2005). Although the group of Regime 2 is the full sample of countries, data is missing for Hong Kong and Nicaragua from Regime 1, and for the Dominican Republic from Regime 3. Further, the aforementioned paper uses a cross-sectional data set with fewer countries than the panel data set of the current paper. In addition, the data in their paper is from 1988 while the data in the current paper is from 1965 to 1990.

Another point worth noting is that CSC appears to be most prevelant at the lowest

[14]The median refers to the median elasticity of substitution for all countries in a specific group over all periods studied.

threshold. Specifically, in the seven groups of countries considered, five of them show significant evidence of CSC. Recall that DPP were able to find more evidence of CSC when skilled labor was defined at a low threshold. The results here show the extreme case when skilled labor is defined as those who have attained some primary schooling.

Given that the nonparametric approach gives observation-specific parameter estimates, it is possible to further analyze the variation across observations. Appendix B gives the median elasticity for each country along with the associated standard error. For countries across the sample, regardless of threshold, there appears to be significant variation in the elasticity of substitution within each measure. Although there is general evidence of CSC across the entire sample, some countries show strong evidence of capital-skill substitutability at each threshold. Again, it is suggested that obtaining a single estimate for an entire panel is not correct for this particular data set. These results show the importance of obtaining observation specific estimates.

## 4.4 Comparison by Time Period

Table 4 presents the median elasticities by year.[15] The results show general support for CSC. However, the results are often insignificant. As in the previous sub-section, one interesting result is that the strongest results for CSC come when skilled labor is defined as those who have some primary education (the fifth threshold). However, different from both DPP and above is that there is some significant evidence of CSC when skilled labor is defined as those who have attained some college (first threshold). Specifically, in two of the six time periods, there is significant evidence of CSC at the median. This anomaly raises a question that deserves further study.

These results are important for at least two reasons. First, it shows weak evidence of CSC at the median during the entire sample period. There appears to be no systematic change across time at the median. Second, the strongest evidence of CSC comes when skilled labor is defined by either a high or a low threshold.

[15] The median refers to the median elasticity of substitution for all countries in a specific time period.

# 5 Conclusion

This paper set out to study the CSC hypothesis in a panel of 73 developed and developing countries using nonparametric kernel techniques. This method allowed for three contributions to the literature. (1) The nonparametric approach allowed for the model to be solved using a single-level production function. (2) It did not require a specific functional form to be assumed for the technology, and (3) it allowed for observation specific estimates of elasticities of substitution. With regard to the first contribution, it was shown that the single-level production function sidestepped the problem of specification choice which arose in the two-level approach. Second, the nonparametric approach made no assumption on the functional form of the technology, nor did it require additional restrictive assumptions such as specifying initial parameters. Finally, as nonparametric methods give parameter estimates for each observation, it was possible to obtain an elasticity of substitution for each observation in the sample.

The inclusion of these techniques on the panel showed general evidence of CSC across the sample. These results appeared to generally hold when examining the quartiles of the elasticities as well as country groups and time medians. That being said, the majority of the evidence for CSC was weak.

Further, the observation specific estimates allowed for deeper analysis of individual countries, groups of countries as well as countries across time. It was found that the elasticities of substitution vary across countries, groups of countries and time periods. These results were shown to be in line with the theories of Goldin and Katz (1998) who suggested that the elasticity of substitution between inputs varies with a country's stage of development and therefore is subject to change over time.

As noted in the introduction, one of the main reasons for studying the CSC hypothesis is to attempt to explain the skilled/unskilled wage differential. Again, if physical capital and skilled labor are found to be more complementary than unskilled labor and physical capital, then an increase in physical capital, *ceteris paribus*, will increase the demand and thus wages for skilled laborers. Unfortunately, many of the results of this study are insignificant and therefore it is difficult to conclude that CSC is *the* factor behind the rise in the skilled/unskilled wage differential.

However, it is also premature to rule out CSC as an important factor in cross-country studies. To help answer to this question, it is important to extend this study in several dimesnions. First, as was stated in Section 2.3.3, imposing constraints from the economic theory on the nonparametric estimators should improve its performance. Also, a longer and wider sample of data may reduce the relatively large standard errors of the nonparametric estimates. That being said, the same could hold true for the estimates in DPP. This may lead to uncovering more cases of significant evidence of CSC.

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**Table 1 -- Stochastic Dominance Tests**

| Null Hypothesis | $G(\sigma_{KN}) = F(\sigma_{KS})$ | $G(\sigma_{KN}) \leq F(\sigma_{KS})$ |
|---|---|---|
| Direct Elasticity of Substitution | | |
| Threshold 1 | 0.000 | 0.000 |
| Threshold 2 | 0.000 | 0.000 |
| Threshold 3 | 0.000 | 0.000 |
| Threshold 4 | 0.000 | 0.954 |
| Threshold 5 | 0.000 | 0.801 |
| | | |
| Allen-Uzawa Elasticity of Substitution | | |
| Threshold 1 | 0.000 | 0.000 |
| Threshold 2 | 0.000 | 0.598 |
| Threshold 3 | 0.000 | 0.888 |
| Threshold 4 | 0.000 | 0.055 |
| Threshold 5 | 0.000 | 0.000 |
| | | |
| Morishima-Blackorby-Russell Elasticity of Substitution | | |
| Threshold 1 | 0.000 | 0.692 |
| Threshold 2 | 0.000 | 0.957 |
| Threshold 3 | 0.000 | 0.997 |
| Threshold 4 | 0.000 | 0.039 |
| Threshold 5 | 0.000 | 0.015 |

NOTES: Probability values are obtained via bootstrapping. The null hypothesis is rejected if the p-value is smaller than some significance level $\alpha$, $(0 < \alpha < 1/2)$. The first column tests the null hypothesis that the two distributions are equal. The second column tests the null hypothesis that the distribution of elasticity of subsitution estimates between physical capital and unskilled labor dominates the distribution of elasticity of substitution estimates between physical capital and skilled labor (CSC).

**Table 2 -- Quartile Values for the Nonparametric Estimates**

| | Q1 | Q2 | Q3 |
|---|---|---|---|
| $\sigma_{KS1}$ | -8.311 | -0.440 * | 3.436 |
| | *22.319* | *0.680* | *0.763* |
| $\sigma_{KS2}$ | -19.713 * | -0.381 | 2.772 |
| | *4.515* | *0.955* | *3.695* |
| $\sigma_{KS3}$ | -5.695 | 0.067 | 3.685 |
| | *4.948* | *0.686* | *5.157* |
| $\sigma_{KS4}$ | -0.873 | -0.050 | 0.651 ** |
| | *0.853* | *0.841* | *1.048* |
| $\sigma_{KS5}$ | -1.281 | 0.010 | 2.233 |
| | *0.665* | *0.689* | *0.370* |
| | | | |
| $\sigma_{KN1}$ | 0.482 | 1.950 | 4.728 |
| | *0.444* | *0.513* | *3.693* |
| $\sigma_{KN2}$ | 0.256 | 2.553 | 7.379 |
| | *3.034* | *8.241* | *1.521* |
| $\sigma_{KN3}$ | -1.588 | 0.917 | 7.933 |
| | *2.996* | *2.087* | *3.894* |
| $\sigma_{KN4}$ | -2.092 | 1.105 | 4.892 |
| | *1.649* | *2.806* | *1.453* |
| $\sigma_{KN5}$ | -0.344 | 3.152 | 26.004 |
| | *0.565* | *1.963* | *14.650* |

NOTES: In the regression function used to estimate each of these Morishima-Blackorby-Russell elasticities, the dependent and independent variables are in levels. Region and time effects are also included. Q1, Q2 and Q3 refer to the first, second, and third quartile, respectively. S1-S5 and N1-N5 refer to the different categories for skilled and unskilled labor, respectively. AICc used for bandwidth selection. Standard errors are listed in italics beneath each estimate. The symbol * (**) corresponds to where the quantile estimates show significant evidence of CSC at the 5% (10%) level.

**Table 3 -- Median Elasticity of Substitution Across Different Groups of Countries**

| Year | $\sigma_{KS1}$ | $\sigma_{KS2}$ | $\sigma_{KS3}$ | $\sigma_{KS4}$ | $\sigma_{KS5}$ | $\sigma_{KN1}$ | $\sigma_{KN2}$ | $\sigma_{KN3}$ | $\sigma_{KN4}$ | $\sigma_{KN5}$ |
|---|---|---|---|---|---|---|---|---|---|---|
| OECD | -0.711 ** | -0.095 | -0.419 | -0.065 | -0.008 | 1.578 | 2.285 | -0.135 | -4.675 | 1.165 |
| | *0.754* | *0.808* | *3.112* | *0.942* | *0.831* | *0.595* | *11.127* | *2.339* | *16.283* | *0.143* |
| Non-OECD | -0.239 | -0.961 * | 0.270 | -0.036 | 0.011 * | 2.401 | 2.708 | 1.966 | 2.819 | 3.739 |
| | *13.485* | *0.381* | *4.106* | *5.699* | *0.244* | *0.778* | *1.048* | *2.221* | *2.717* | *1.627* |
| Latin America | 0.369 | 2.231 | 1.612 | -0.462 * | 0.005 * | 2.510 | 2.605 | 3.429 | 4.302 | 3.796 |
| | *0.339* | *1.094* | *1.060* | *1.015* | *0.440* | *0.976* | *1.369* | *1.752* | *0.787* | *0.475* |
| Africa | -11.324 | -72.931 ** | -3.104 | 0.350 | 0.051 | 2.327 | 7.798 | 3.972 | 2.043 | 4.539 |
| | *7.742* | *39.030* | *8.378* | *8.269* | *2.609* | *4.088* | *2.373* | *22.983* | *5.057* | *1.071* |
| Regime 1 | -0.147 | 0.005 | 0.181 | -0.386 | -0.266 * | 1.718 | 1.378 | 0.103 | 0.507 | 7.310 |
| | *5.228* | *2.295* | *0.649* | *0.635* | *0.226* | *3.761* | *0.790* | *6.728* | *0.492* | *0.843* |
| Regime 2 | 2.207 | 1.484 | 1.155 | 0.025 | -0.045 * | 2.027 | 1.810 | 1.911 | 2.505 | 1.800 |
| | *1.895* | *1.603* | *1.553* | *1.147* | *0.265* | *0.515* | *0.766* | *0.894* | *0.615* | *0.262* |
| Regime 3 | 0.035 | -0.173 | 0.485 | -0.018 | 0.003 * | 1.239 | 1.416 | 0.147 | 0.735 | 1.723 |
| | *1.439* | *0.915* | *94.814* | *3.640* | *0.185* | *1.030* | *0.954* | *2.429* | *2.191* | *0.207* |
| All | -0.440 * | -0.381 | 0.067 | -0.050 | 0.010 | 1.950 | 2.553 | 0.917 | 1.105 | 3.152 |
| | *0.680* | *0.955* | *0.686* | *0.841* | *0.689* | *0.513* | *8.241* | *2.087* | *2.806* | *1.963* |

NOTES: In the regression function used to estimate each of these Morishima-Blackborby-Russell elasticities, the dependent and independent variables are in levels. Region and time effects are also included. The median refers to the median elasticity for all countries over all periods for a particular group. S1-S5 and N1-N5 refer to the different categories for skilled and unskilled labor, respectively. AICc used for bandwidth selection. OECD includes countries which were in the OECD as of 1990, whereas "Regime 1, 2, and 3" includes the countries of Regimes 1, 2 and 3 in Table 3 of Papageorgiou and Chmelarova (2005). Standard errors are listed in italics beneath each estimate. The symbol * (**) corresponds to where the median estimates exhibit significant evidence of CSC at the 5% (10%) level.

**Table 4 -- Median Elasticity of Substitution Across Countries for Each Time Period**

| Year | $\sigma_{KS1}$ | $\sigma_{KS2}$ | $\sigma_{KS3}$ | $\sigma_{KS4}$ | $\sigma_{KS5}$ | $\sigma_{KN1}$ | $\sigma_{KN2}$ | $\sigma_{KN3}$ | $\sigma_{KN4}$ | $\sigma_{KN5}$ |
|---|---|---|---|---|---|---|---|---|---|---|
| 1965 | -0.467 | 0.194 | 1.287 | -0.099 ** | 0.006 | 2.329 | 2.495 | 2.653 | 2.259 | 3.241 |
| | *0.761* | *1.575* | *2.785* | *0.300* | *0.440* | *4.088* | *0.837* | *3.931* | *1.043* | *2.413* |
| 1970 | -0.673 | 0.393 | -3.922 | -0.085 | -0.305 * | 2.264 | 2.956 | 0.062 | 1.240 | 3.411 |
| | *7.202* | *3.090* | *3.305* | *1.692* | *0.328* | *0.694* | *0.797* | *2.864* | *0.745* | *0.359* |
| 1975 | -1.562 * | -0.915 | -0.368 | -0.053 | -0.327 * | 1.962 | 2.568 | 0.059 | 1.269 | 2.916 |
| | *0.541* | *2.071* | *1.598* | *0.441* | *0.328* | *0.559* | *0.577* | *1.781* | *0.616* | *0.570* |
| 1980 | -0.980 | -1.252 | 0.035 | 0.040 | 0.071 * | 1.685 | 3.189 | 0.707 | 0.542 | 3.382 |
| | *2.625* | *4.633* | *0.428* | *0.151* | *0.109* | *0.769* | *12.465* | *0.772* | *0.764* | *0.359* |
| 1985 | -1.191 ** | -2.246 | -1.937 | 0.015 | -0.037 | 1.008 | 2.786 | 0.492 | 0.918 | 1.309 |
| | *0.769* | *2.774* | *35.846* | *1.777* | *0.048* | *0.413* | *0.751* | *1.612* | *2.035* | *3.921* |
| 1990 | 1.956 | -0.988 * | 2.716 | -0.453 | 1.197 | 2.090 | 0.990 | 2.041 | 0.487 | 11.911 |
| | *15.370* | *0.381* | *1.915* | *2.316* | *0.490* | *0.657* | *0.497* | *1.727* | *0.274* | *23.328* |
| All | -0.440 * | -0.381 | 0.067 | -0.050 | 0.010 | 1.950 | 2.553 | 0.917 | 1.105 | 3.152 |
| | *0.680* | *0.955* | *0.686* | *0.841* | *0.689* | *0.513* | *8.241* | *2.087* | *2.806* | *1.963* |

NOTES: In the regression function used to estimate each of these Morishima-Blackorby-Russell elasticities the dependent and independent variables are in levels. Region and time effects are also included. The median coefficient for each year over all countries is given. S1-S5 and N1-N5 refer to the different categories for skilled and unskilled labor, respectively. AICc used for bandwidth selection. Standard errors are listed in italics beneath each estimate. The symbol * (**) corresponds to where the median estimates exhibit significant evidence of CSC at the 5% (10%) level.