Economic Development and the Return to Human Capital: An Approach based on a Smooth Coefficient Semiparametric Model *

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ABSTRACT

This paper investigates the impact of human capital to the process of economic growth by allowing the contribution of traditional inputs (capital and labor) as well as that of human capital to vary both across countries and time. The former is accomplished by constructing an index of TFP growth for traditional inputs, while the latter through semiparametric methods. We derive estimates of the output elasticity and social return to human capital for 51 countries at various stages of economic development.

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1 Introduction

Following the pioneering work of Becker (1964) and Schultz (1960), much attention has been devoted by both researchers and policy makers to uncovering the contribution of human capital to the process of economic growth and development. The fundamental question is the extent to which investment in human capital contributes to raising income. At the micro level, one of the persistent findings of the literature is that human capital formation, as manifested in improvements in education, tends to raise wages. Numerous studies have estimated a wage equation according to which an individual's wage rate is regressed on years of schooling and experience (commonly referred to as Mincerian wage functions). These studies have consistently yielded significant estimates of the return to education for a variety of countries at different stages of economic development.

Human capital accumulation ought to raise income at the aggregate (macro) level, a proposition put forward by Schultz (1960) and subsequently explored both theoretically and empirically. Evidence at the macro level has been mixed. Studies such as Barro (1991), Bils and Klenow (2000), Mankiw *et al.* (1992) and others use enrollment rates and find a positive and significant contribution for human capital to the growth of output (GDP). Benhabib and Spiegel (1994), Kyriacou (1991), Lau *et al.* (1991) and Pritchett (1996b), however, find an insignificant or even negative contribution for the stock of human capital (mean years of schooling). The estimated effect for human capital does not hinge on the way it is defined (as stock or flow).[1]

[1] Early studies tended to use a flow measure (enrollment rates) while more recent studies have used a stock measure (mean years of schooling derived from cumulating past enrollment rates).

For example, Barro and Sala-i-Martin (1995) find the impact of enrollment rates to be insignificant while mean years of schooling has a positive and significant effect on economic growth. Kalaitzidakis *et al.* (2001) introduce the various definitions of human capital into the growth process via the Mankiw *et al.* (1992) framework. They use semiparametric techniques and find that the growth-human capital nexus is quite complex. They suggest that there are substantial nonlinearities in the growth-human capital relationship that linear models of the existing literature are unable to detect. Given the overwhelming evidence on the income-enhancing effects of human capital at the micro level, the equivocal results of the macro studies are puzzling.

The inconsistency between the two lines of research has generated considerable interest and attempts to reconcile them by Krueger and Lindahl (2000) and Topel (1999): the former suggest that the human capital variable (changes in mean years of schooling) in growth regressions conveys very little signal due to the imprecise measure of education and the latter raises the possibility that the specification of growth regressions with respect to human capital (double logarithmic) is inappropriate. In this paper we reconcile the two approaches by taking issue with the main assumptions of the cross-country growth literature: same technology in 'traditional' inputs (capital and labor) and a uniform impact of human capital on aggregate output both across countries and time. Even a cursory look at the data in Table A.1 reveals that the contribution of capital and labor is not constant: the output share of labor (the output elasticity in the Cobb-Douglas production function) varies substantially across the 51 countries in our sample from a low of 42.5 to a high of 74.6 percent.[2] Recent theoretical work (Azariadis

[2] We have computed this share by taking into account the contribution of both employees and the self employed (the Appendix provides details).

and Drazen, 1990) has demonstrated that the way in which human capital impacts the growth of output differs across countries. In particular, threshold externalities may exist as a result of attaining a "critical mass" in human capital and, therefore, economies that are similar in terms of technology or preferences may display substantial differences in growth rates if they lie on either side of the threshold. In Durlauf (1993), local technological spillovers generate multiple growth equilibria characterized by differences in the way in which the traditional inputs are employed in aggregate production.

Our study aims to remedy both deficiencies. In the first place we use annual data for 1971-1987 for 51 countries to calculate a 'traditional' index of total factor productivity (TFP) growth. This index contains only the contribution of the 'traditional' inputs (capital and labor). The novelty of our approach is that it eschews the estimation of a production function with the implicit assumption that the output contribution of capital and labor is constant. This is an important attribute because all previous studies (including ours) contain countries at widely differing stages of economic development, obviating the need to relax the assumption of a constant contribution both intra and inter temporally. Next, we use this index to evaluate the impact of human capital growth on the growth of TFP. We accomplish this via semiparametric methods that allow the effect of human capital accumulation on economic growth to be nonlinear. Given our evidence (discussed in subsequent sections) that significant nonlinearities describe the economic growth-human capital nexus, parametric methods are likely to detect an insignificant effect for human capital because parametric formulations misspecify the complex nature of the relationship and yield estimates that are biased.

An important contribution of our work is the construction of estimates of the elasticity of output with respect to human capital that display a rather large variation across countries, casting doubt on the equality assumption in the literature. Moreover, for a number of the developing economies in our sample, human capital (mean years of schooling) has no significant effect on aggregate output, a possibility mentioned in the literature (e.g. Pritchett, 1996b) but not explored in a systematic fashion empirically. Our methodology also allows us to derive an estimate of the social rate of return to human capital from aggregate data on output and inputs. We find substantial differences in rates of return according to a country's stage of economic development. In general, social rates of return to human capital for the low/middle income economies are not higher than those of the high income economies. It is noteworthy that this conjecture is not consistent with the conventional wisdom that factors in scarce supply should command higher rates of return. It should be emphasized that the conventional view is predicated on identical technologies and ignores external effects, both of which are taken into consideration by our methodology.

In the next section we present our methodology. We construct a traditional index of TFP growth that does not rely on the estimation of a production function with the concomitant assumption of constant capital and labor contributions across countries and time. In the third section we employ a semiparametric estimation methodology that allows the effect of human capital on TFP growth to be nonlinear. This methodology enables us to derive country (and time) specific estimates of output elasticities and social rates of return for human capital. The final section concludes the paper.

2 Methodology

The treatment of human capital in cross-country (macro) studies falls into three main categories: (a) a production function is combined with equations for the accumulation of reproducible factors to arrive at equations for the steady state of per capita income and the transition process to the steady state (e.g. Mankiw *et al.*, 1992 and the substantial literature spawned by this study); (b) a production function that includes human capital as either an input or as a determinant of total factor productivity is estimated directly (e.g. Benhabib and Spiegel, 1994; Edwards, 1998; Pritchett, 1996b); and (c) specific values are assigned to the coefficients of the production function (the shares of inputs) to arrive at an estimate of the residual which is then evaluated, along with the factors of production (including human capital), for their contribution to differences in the level or growth of per capita GDP (e.g. Hall and Jones, 1999; Klenow and Rodríguez-Clare, 1997). Most of these studies are based on very restrictive assumptions: a Cobb-Douglas production function with Hicks-neutral technology. By contrast, our study relies on a general framework. We assume that a general production function describes the technology of country i at time t as follows:

$$Y = f(K, E, H, t) \tag{1}$$

where Y, K, and E represent the amounts of total output, physical capital, and effective or human-capital augmented labor, respectively, H is average human capital (mean years of schooling per person of working age) and t is a technology index measured by the time trend.

Total differentiation of (1) with respect to time and division by Y yields:

$$\widehat{Y} = \widehat{A} + \varepsilon_K \widehat{K} + \varepsilon_E \widehat{E} + \varepsilon_H \widehat{H} \tag{2}$$

where $(\widehat{\ })$ denotes a growth rate, $\widehat{A} = (\partial f/\partial t)/Y$ is the exogenous rate of technological change and $\varepsilon_Q = \partial \ln Y/\partial \ln Q$ $(Q = K, E, H)$ denotes output elasticity. The last term in (2) measures the externality effect to human capital accumulation. This effect is emphasized by recent endogenous growth models initiated by Lucas (1988). Assuming a perfectly competitive theory of distribution, the output elasticities of effective labor and capital should be equal to the observed income shares of labor, s_{YL}, and capital, s_{YK}.[3] Equation (2), however, is not useful for empirical purposes because the growth rate of effective labor $\widehat{E}$ is not observable.

Assuming that the effective labor input is a function of the labor force and average human capital, or

$$E = g(L, H), \tag{3}$$

we can decompose $\widehat{E}$ as:

$$\widehat{E} = \eta_L \widehat{L} + \eta_H \widehat{H} \tag{4}$$

where η_L and η_H are effective labor elasticities with respect to labor and average human capital, respectively. Substituting (4) in (2) we have:

$$\widehat{Y} = \widehat{A} + \varepsilon_K \widehat{K} + \varepsilon_E \eta_L \widehat{L} + (\varepsilon_E \eta_H + \varepsilon_H) \widehat{H} \tag{5}$$

By contrast with (2), the last term in parentheses in (5) measures the total effect of human capital, while the output elasticity of raw labor is $\varepsilon_E \eta_L$. Direct estimation of (5) corresponds to the well-known growth accounting

[3] The income share of labor can be defined in two ways: the income share of effective labor (E) or the income share of 'traditional' or workforce labor (L). These two are equal since the value of labor (the numerator of the income share) is the same independently of the definition of the labor input as L or E (the corresponding price and quantity indices, however, will differ).

methodology. For instance, Benhabib and Spiegel (1994) obtain estimates on $\widehat{K}$, $\widehat{L}$ and $\widehat{H}$ of 0.46, 0.21 and 0.06, respectively, with only the estimate on $\widehat{K}$ being significant; other researchers report similar findings. Estimating equation (5) with data from 51 countries during 1971-87 we obtain the following results (data sources and construction is described in the Appendix; heteroskedasticity-consistent standard errors are shown in parentheses):

$$\begin{array}{lllll} \widehat{Y} = \underset{(0.002)}{0.003} & + \underset{(0.033)}{0.583}\widehat{K} & + \underset{(0.098)}{0.178}\widehat{L} & - \underset{(0.071)}{0.010}\widehat{H} & \overline{R}^2 = 0.27, \quad n = 867. \end{array}$$

The magnitude (and significance) of our estimates is very similar to the cited studies. We also estimated equation (5) with cross section data (the method chosen by the cited studies) and by averaging our panel data into three subperiods: 1971-1976, 1977-1982 and 1983-1987.[4] These results are consistent with the findings in the literature: human capital accumulation does not seem to exert a positive effect on economic growth.

As mentioned previously and by several authors (e.g. Temple 1999), an important criticism of estimating a model such as (5) is the assumption that the contribution of inputs is the same across countries and time so the estimated parameters represent an 'average' contribution. In the remainder of this paper we address this issue through an alternative specification that accounts for differing contributions of all productive inputs. In the first instance, we construct an index of TFP growth for our panel that contains

[4] The estimates for $\widehat{K}$, $\widehat{L}$ and $\widehat{H}$ with cross section data (51 observations) are 0.54, 0.33 and -0.06, respectively, with the estimate on $\widehat{H}$ insignificant and the other two retaining the same degree of significance as those in the text. The panel estimates based on average growth rates (153 observations) are 0.52, 0.26 and -0.05, with the coefficient on $\widehat{H}$ once more insignificant. We also estimated the model with country- and year-specific dummy variables with little change in the magnitude or significance of the estimates of $\widehat{H}$.

only the traditional inputs. This index allows the contribution of capital and labor to differ both intra and intertemporally and to be dictated by the data. We define a Törnqvist index of TFP growth for country i in year t as follows:

$$\widehat{TFP}_{it} = \widehat{Y}_{it} - s_{Eit}\widehat{L}_{it} - s_{Kit}\widehat{K}_{it} \tag{6}$$

where $s_{Eit} = 0.5(S_{Lit} + S_{Lit-1})$ and $s_{Kit} = 0.5(S_{Kit} + S_{Kit-1})$ are weighted averages of the cost shares of labor and physical capital (S_{Lit} and S_{Kit}, defined in the Appendix) and $\widehat{Q}_{it} = \ln Q_{it} - \ln Q_{it-1} (Q = Y, L, K)$.[5] This measure of TFP contains the component of output growth that cannot be explained by the growth of 'traditional' inputs (K and L). This index will be an exact index of exogenous technological change under certain conditions (see Diewert, 1976) and as long as the production function contains only the traditional inputs. The production function underlying this index is a general translog. It should be stressed, however, that if human capital enters the production function as in (1), this index is a biased index of technological change and, therefore, variations in $\widehat{H}$ will affect TFP growth as defined in (6). In what follows we present a methodology for estimating this effect.

Subscripting equation (5) by country and year (it), taking a discrete approximation of the continuous growth rates and adding (6) to it we have:

$$\begin{aligned} \widehat{TFP}_{it} &= \widehat{A}_{it} + \left[(\varepsilon_{Kit} - s_{Kit})\widehat{K}_{it} + (\varepsilon_{Eit}\eta_L - s_{Eit})\widehat{L}_{it}\right] \\ &\quad + (\varepsilon_{Eit}\eta_{Hit} + \varepsilon_{Hit})\,\widehat{H}_{it} \end{aligned} \tag{7}$$

where the first term ($\widehat{A}_{it}$) is the exogenous rate of technological change, and the final term in parentheses is the total contribution of human capital. The

[5] The cost shares of effective and 'traditional' labor are the same independently of how we define labor because labor cost should be the same. Thus $s_{Eit} \equiv s_{Lit}$, where E and L denote, as before, an index of effective and 'traditional' labor input.

latter is made up of two components: the first is the direct or private effect of human capital and the second is the indirect or externality effect. The term in brackets is the scale effect. Under constant returns to scale, output elasticities will be equal to the cost shares and the term in brackets will be equal to zero if $\eta_L = 1$.[6] It can be shown that the first order conditions of standard cost minimization with respect to physical capital and labor (taking average human capital as given) imply that

$$\varepsilon_{jit} = \rho s_{jit}, \quad j = K, E \tag{8}$$

where $\rho = \varepsilon_{CY}^{-1}$ is the elasticity of returns to scale of capital and labor and $\varepsilon_{CY} = (\partial C/\partial Y)/(Y/C)$ is cost flexibility.

Of central importance to our study is the final term in (7) that captures the contribution of human capital to aggregate production. We model this as a general unknown function $\theta(\cdot)\widehat{H}_{it}$. Details on the specification and estimation of the $\theta(\cdot)$ function will be provided in the following section. Using the above formulation for $\theta(\cdot)$ and (8), (7) can be written as:

$$\widehat{TFP}_{it} = \widehat{A}_{it} + \alpha\widehat{M}_{it} + \theta(\cdot)\widehat{H}_{it} \tag{9}$$

where $\alpha = (\rho - 1)$ and $\widehat{M}_{it} = s_{Kit}\widehat{K}_{it} + s_{Eit}\widehat{L}_{it}$. Estimation of (9) allows testing the hypothesis of non constant returns to scale in capital and labor ($\alpha \neq 0$). Moreover, it allows human capital to influence TFP growth in a nonlinear fashion.

[6] The condition $\eta_L = 1$ will be true if (3) is linear homogeneous in L or the production function for effective labor can be written as $g(L, H) = L\varphi(H)$, where $\varphi(H)$ is any function of H. Many popular models belong to this class of effective labor production function. For example, Lucas (1988) postulates that $g(L, H) = LH$. Another possibility is a Mincerian type production function $g(L, H) = Le^{\phi(H)}$ assumed by Hall and Jones(1999).

In the following section the nonlinear aspects of human capital growth are investigated systematically via semiparametric estimation. Equation (9) forms the basis of our empirical analysis. It is important to note that the form and interpretation of (9) depends on the definition of the TFP growth index in (6). Our objective is to identify the total effect of human capital (direct plus indirect) under minimal assumptions. Therefore in (6) we define an index which can be constructed from observable data and can yield estimates of the total effect. For instance, instead of (6) we can define a TFP growth index by subtracting from output growth the (cost-share) weighted growth rates of effective labor and physical capital, $\widehat{TFP}_{it} = \widehat{Y}_{it} - s_{Eit}\widehat{E}_{it} - s_{Kit}\widehat{K}_{it}$ or by subtracting from output growth the (cost-share) weighted growth rates of labor and capital where the labor weight is based on the cost share of unskilled or raw labor s^b_{Lit}, $\widehat{TFP}_{it} = \widehat{Y}_{it} - s^b_{Lit}\widehat{L}_{it} - s_{Kit}\widehat{K}_{it}$. These alternative definitions of the TFP index will not meet our objectives. Using these alternative indices would require information on effective labor or the raw labor cost share, neither of which is directly observable. It could be argued, however, that these can be obtained by making assumptions about the private contribution of human capital or by using estimates from micro studies. Clearly, if these assumptions or estimates are not correct they may bias the total effect of human capital. In summary, defining a TFP growth index as in (6) that is based on observable data appears to us appropriate.

3 Estimation and Empirical Results

3.1 Estimation Method

In order to estimate equation (9) we model $\widehat{A}_{it}$ (exogenous growth of technological change) as a function of country- and year-specific dummy variables. Country-specific dummies (D_i) capture idiosyncratic exogenous technological change and time-specific dummies (D_t) capture the procyclical behavior of TFP growth. In alternative specifications we include political and economic freedom and a country's trade orientation as additional determinants of TFP growth. The rationale for this is that increased exposure to international trade promotes technology absorption and boosts productivity. Edwards (1998) provides evidence linking outward orientation (Z_1) with TFP growth. The role of institution building as a determinant of long-run economic performance has received considerable attention recently. Rodrik (2000) discusses five types of institutions: property rights, regulatory institutions, institutions for macroeconomic stabilization, institutions for social insurance and institutions of conflict management. He argues that building institutions can be thought of as a form of technology transfer which allows increased productivity. Participatory democracy is a meta-institution that helps build better institutions. He provides evidence that participatory democracy improves economic performance both in terms of higher long-run growth rates and short-term stability. We include two measures of participatory democracy: an index of political freedoms (Z_2) and civil freedoms (Z_3).[7]

As for the unknown function $\theta(\cdot)$ we estimate two alternative specifica-

[7] Details on the measurement of the political and civil freedom indexes and outward orientation are provided in the Appendix.

tions. First, we postulate that it depends on the level of human capital. In the alternative specification, in addition to the level of human capital it also depends on other economy characteristics (Ω). Appending an error term, u_{it}, equation (9) then becomes:

$$\begin{aligned} \widehat{TFP}_{it} &= a_0 + \sum_{i=1}^{N-1} a_i D_i + \sum_{t=1}^{T-1} a_t D_t + \sum_{s=1}^{3} b_s Z_{sit} \\ &\quad + \alpha \widehat{M}_{it} + \theta(H_{it}, \Omega_{it}) \widehat{H}_{it} + u_{it} \\ &= X_{it}\beta + \theta(H_{it}, \Omega_{it}) \widehat{H}_{it} + u_{it}, \end{aligned} \tag{10}$$

where $X_{it} = (D_i, D_t, Z_{sit}, \widehat{M}_{it})$ and the error term satisfies $E(u_{it} \mid X_{it}, H_{it}, \widehat{H}_{it})$ $= 0$.

The central issue in (10) is the estimation of the $\theta(\cdot)$ function. The estimation approach adopted here is based on the smooth coefficient semiparametric model (see Fan, 1992; Fan and Zhang, 1999; and Li et al., 2001). It is a generalization of varying coefficient models and follows the local polynomial linear regression of Stone (1977) and Fan (1992) as well as the widely used Nadaraya-Watson constant kernels.

The general description of the method follows. The data are given as $\{Y_i, W_i\}$, $i = 1, ...n$, a realization from an *i.i.d.* random vector $\{Y, W\}$. The covariates are defined on $\mathcal{W} \subseteq \Re^q$. We are interested in estimating the unknown regression function, expressed as $E(Y|W = w) = \varphi(w)$, nonparametrically. We accomplish this by introducing some potentially relevant information expressed in terms of a parametric function $m(W, \gamma)$. One can then proceed by minimizing the following local nonlinear least squares criterion function over the parameter space:

$$Q_n(w, \gamma) = n^{-1} \sum_{i=1}^{n} \{Y_i - m(W_i, \gamma)\}^2 K_A(W_i - w) \tag{11}$$

where $K_A(.) = \det(A)^{-1}K(A^{-1}.)$, $K(.)$ is a real-valued multivariate kernel and A is a nonsingular bandwidth matrix $q \times q$.

In our estimation problem, let us define $V_i = \{H_i, \Omega_i\}$. Then in (11) we have $W_i = \{X_i, V_i\}$, where for notational simplicity we suppress the observation subscript it as $i = 1, ...n$, with $n = N \times T$. The regression function is given as

$$E(Y|X = x, V = v, \widehat{H} = \widehat{h}) = x\beta + \theta(v)\widehat{h} \tag{12}$$

In general $\theta(\cdot)$ is an unknown function and we approximate it by a second order Taylor series at any given point, say v_0, as

$$\theta(v) \simeq \theta(v_0) + \theta^{'}(v_0)^T(v - v_0) + (1/2)(v - v_0)^T\theta^{''}(v_0)(v - \nu_0) \tag{13}$$

where $\theta^{'}(v_0)$ is a 2×1 vector of first derivatives and $\theta^{''}(v_0)$ is a 2×2 matrix of second derivatives evaluated at v_0. We let $m(W, \gamma)$ be equal to

$$m(X_i, V_i, \widehat{H}_i, \gamma) = X_i\beta + \left[(\delta_1 + \delta_2^T(V_i - v) + (V_i - v)^T\delta_3(V_i - v)\right]\widehat{H}_i \tag{14}$$

where $\gamma = (\beta, \delta_1, \delta_2, \delta_3)$ and we form the objective function given in (11). The parameter estimates of $\delta_1, \delta_2, \delta_3$ will give us the estimates of $\theta(\cdot)$, the vector of its first derivatives and the matrix of its second derivatives respectively.

Estimation results are presented in Table 1. The first column of Table 1 shows estimates of the model in (10) assuming that θ is a constant i.e., linear contribution for human capital. In this specification, the exogenous rate of technological change depends only on country- and time-specific fixed effects. Column 5 of Table 1 shows the estimates of the linear component of the semiparametric counterpart to this model. We use a standard multivariate kernel density estimator with a Gaussian kernel and the rule of thumb suggested by Silverman (1986) as the choice of bandwidth. The bandwidth for variable W_i is chosen as $s_{w_i} n^{-\frac{1}{4+q}}$, where s_{w_i} denotes the estimate of the standard deviation of variable W_i and q is the dimension of the kernel. The non-parametric component of equation (10), the estimates of function θ, is examined using graphical tools. We present their density function in Figure 1. This density function is estimated using a Gaussian kernel and the same rule of thumb for the choice of bandwidth as the semiparametric model.

The estimate of scale (α) is insignificant in both linear and semiparametric models; this is true using either method for constructing the user cost of capital (see the Appendix). Therefore the null of constant returns to scale (in labor and capital) cannot be rejected. In what follows we present results on the assumption that payments to capital and labor exhaust total output; results using the other methods for constructing the user cost of capital are similar. Table 1 also shows that the coefficient estimate for human capital in the linear model is insignificant as reported previously in the literature. On the other hand the estimates of θ in Figure 1 reveal that the effect of human capital is not constant across countries and time but varies considerably. The vast majority of the elasticity estimates lie in the range 0-0.2.

It is generally acknowledged that the measurement of the contribution of labor in national income accounts is beset with errors. In order to reduce the possibility that our results are driven by measurement error, we regressed the observed labor share on country characteristics such as the capital-labor ratio and per capita GDP. We then used estimates from this regression as our measure of the share of labor in national income. Results using this measure are shown in columns 2 and 6 of Table 1, corresponding to the linear and nonlinear models, respectively. The estimates of density function for this specification are shown in Figure 2. The results with the 'smoothed' labor share are very similar to those using the observed labor shares. In what follows, we report results based on 'smoothed' labor shares. Results based on measured labor shares are quite similar and are available on request.

We have performed a number of robustness checks on our results. First, there are two widely recognized limitations that hamper estimation whether one attempts to estimate a TFP growth model as in (9) or a production function directly as in (5). The first concerns the aggregation of different types of labor and capital, an issue raised by Jorgenson and Griliches (1967) and recently by Barro (1999). Data limitations prevent us from pursuing this. The second is endogeneity. Estimating equation (10) may be problematic due to the possible endogeneity of $\widehat{H}$. This issue has been raised previously in the TFP growth literature (Griliches, 1973, contains a succinct discussion). The growth of human capital may respond to exogenous shocks to productivity growth (the $\widehat{A}$ term in (9)) and therefore the estimated coefficient on $\widehat{H}$ would proxy, in part, for exogenous technological progress.[8] By way of accounting for this endogeneity, we have instrumented for $\widehat{H}$. Finding suitable instruments for $\widehat{H}$ presents problems. We have used the dummy variables (D_i and D_t) as well as (twice) lagged values of (the logarithm of) human capital, the quantity and the price of labor as instruments. We have also experimented with other combinations of instruments (e.g. lagged values of the quantity of output or capital and the share of labor) arriving at similar results. In order to obtain an optimal instrument for $\widehat{H}$, the dummy variables are entered parametrically while the other three instruments are entered nonparametrically. The instrumental values of $\widehat{H}$ are then used in equation (10). The results are similar to those reported

[8] Moreover, if human capital and the traditional inputs are correlated, the effect of human capital on TFP growth will be biased (see, for instance, Bartelsman, 1990).

above.[9]

Finally, we have tested the semiparametric formulation against a general nonparametric model via a test proposed by Fan and Li (1996). The null hypothesis of the semiparametric specification can be expressed as $E(Y \mid W) = X_{it}\beta + \theta(V_{it})\widehat{H}_{it}$ and the alternative hypothesis as $E(Y \mid W) = f(W) \neq X_{it}\beta + \theta(V_{it})\widehat{H}_{it}$. Under the null hypothesis, this nonparametric functional form ($NPFF$) test statistic follows the asymptotic standard normal distribution. The value of the Fan-Li $NPFF$ statistic is 0.637. Therefore, the null hypothesis of a semiparametric specification cannot be rejected against the alternative.

The other two specifications in Table 1 introduce political and civil freedoms and trade orientation as determinants of TFP growth. The specifications in columns 3 and 7 (linear and nonlinear, respectively) assume that $\theta(\cdot)$ (or, as will be argued shortly, the elasticity of human capital) depends on the level of human capital alone. The specifications in columns 4 and 8 assume that elasticity depends on human capital and trade orientation. That the elasticity (and consequently the rate of return) of human capital

[9] One objection to the use of annual data to uncover the aggregate impact of human capital is that such data may capture year-to year (or 'cyclical') effects rather than long-run (or 'growth') effects. We have attempted to capture some of the 'cyclical' effects through the inclusion of year dummy variables in all our models. In addition and in order to check the consistency of our results, we have reestimated the model averaging our data over three periods: 1971-76, 1977-82 and 1983-87. The use of such data may help in identifying more accurately the long-run impact of human capital by increasing the signal to noise ratio in the data. The disadvantage is that sample size is substantially reduced (from 867 to 153 observations) which will reduce the efficiency of the semiparametric estimates. The results (available on request) are qualitatively very similar to the complete sample.

should depend on the level of human capital is straightforward. What is less straightforward and requires explanation is why the output elasticity of human capital should depend on a country's trade orientation. Pissarides (1997) claims that the return to human capital increases relative to the return to unskilled labor (as manifested by a widening gap in wages between skilled and unskilled labor) as developing countries liberalize their trade regime. This is due to the transfer of skill biased technology to developing economies from developed countries as these economies increase their exposure to the world economy. All the economies that have moved towards increased trade openness during our sample period are low or middle income. We model this effect for the linear model in column 4 by introducing an interaction term between human capital and trade orientation.

The results in Table 1 show no evidence that greater political or civil freedoms promote TFP growth in either linear or semiparametric models, but there is marginal evidence on the beneficial effect of outward orientation on the growth of productivity. On the other hand the estimates of θ in Figures 3 and 4 (corresponding to the models in columns 7 and 8 of Table 1) reveal that the effect of human capital is not constant across countries and time but varies considerably. The density of θ in figure 4 is bimodal. The two modes, around -0.39 and 0.18, correspond to closed and open economies, respectively. The right mode is clearly the dominant one; it corresponds to outward oriented economies.

3.2 The Output Elasticity of Human Capital

Of key importance to our work is the derivative of TFP growth with respect to human capital growth or $\theta(\cdot)$. It is important to note that this derivative corresponds to the output elasticity of mean years of schooling (H), i.e.,

$$\varepsilon_{YHit} = \frac{df}{dH_{it}} \frac{H_{it}}{Y_{it}} = \varepsilon_{Eit}\eta_{Hit} + \varepsilon_{Hit} = \theta(\cdot). \tag{15}$$

Figure 5 plots point-wise estimates of the output elasticity, $\theta(\cdot)$, on the vertical axis and the level of human capital, H_{it}, on the horizontal. Also, the average output elasticity for each country is reported in Table 2 along with its standard error. Both the point-wise estimates of Figure 5 and the average elasticities of Table 2 are given for the specification in column 6 of Table 1. Very similar results (available on request) are obtained for the specifications in columns 5 and 7 of Table 1. The average elasticities lie within a relatively wide but 'sensible' range: 0.01 to 0.30. There is a large variation in the estimates of elasticity across countries casting doubt on the widespread assumption in the literature of uniform elasticity across countries. The elasticity estimates are largest for the high-income economies: the (unweighted) average elasticity for the twenty highest income economies in our sample is 0.14. Figure 5 indicates that for the low and middle income economies (with relatively lower levels of human capital) there are decreasing returns to scale for human capital while for the higher income economies there are constant and/or increasing returns.

In many developing economies, our estimate of the output elasticity is low. Of the thirty-one countries in Table 2 identified by the World Bank (1989) as low- or middle-income in 1987, our elasticity estimate is insignificant for ten. It may be that structural obstacles prevent the efficient usage of human capital in developing countries. It is well known that human capital requires complementary 'advanced' technologies, a factor in scarce supply in developing economies but a factor that can be made available through increased exposure to international trade. The lack of complementary technologies implies that increased levels of education are frequently directed towards socially-wasteful or directly-unproductive activities or may come up against greater incidence of unemployment, a point noted by Pritchett (1996b) and Krueger and Lindahl (2000). There is certainly a large body of anecdotal evidence describing university graduates in developing countries devoting their talents to rent-seeking activities or frequently becoming unemployed (or underemployed in work that is not commensurate with their level of education) upon graduation and are forced to enter the unofficial economy.

Figure 6 shows point wise estimates of the elasticity of human capital for the model in column 8 of Table 1, i.e. when we assume that a country's outward orientation (as well as its level of human capital) is a determinant of the human capital elasticity. One interesting conclusion emerges from Figure 6. Two distinct non linear relationships can be observed: the upper of the two curves corresponds to economies that are open ($Z_1 = 1$) while the lower corresponds to economies that are closed ($Z_1 = 0$). It is clear that, *ceteris paribus*, the elasticity of human capital is higher the more open an economy. To the best of our knowledge this is the first systematic empirical confirmation of the oft cited proposition that greater exposure to international trade brings access to foreign technology that complements human capital and raises its marginal contribution to aggregate production.

3.3 The Social Rate of Return to Human Capital

As mentioned in the introduction, numerous studies have estimated the return to human capital (education) on the basis of micro survey data. Psacharopoulos (1994) summarizes the literature and provides indicative rates of return for various countries. On the other hand, the literature provides no studies of estimates of the return to human capital based on aggregate (macro) data for a wide cross section of economies. Krueger and Lindahl (2000) and Topel (1999) attempt to link the micro studies with the cross-country growth accounting literature but their methodology does not allow country-specific estimates of the return to human capital.

The methodology presented in this paper allows us to retrieve an estimate of the social return to human capital that is country (and time) specific. This is equal to the marginal benefit over the marginal cost of an additional unit of human capital. The marginal benefit is defined as the additional units of output per worker gained (or lost) as a result of a unitary increase in human capital (mean years of schooling), or, using (15), $\varepsilon_{YH}\frac{Y/L}{H}$. The marginal cost of an additional unit of human capital is assumed to equal the real wage rate for unskilled or 'raw' labor, P_L^b/P_Y, the opportunity cost of schooling. Computing the wage rate for raw labor (P_L^b) is problematic because there are no widely available estimates that are comparable across countries. In the Appendix we present a computation method that is consistent with estimated rates of return to education from micro studies.

Bils and Klenow (2000) have assembled representative returns (in terms of higher wages) to an additional year of schooling from a variety of sources. These returns are from estimates of Mincerian wage functions with micro data; this is the private return to education. They are available for thirty three of the 51 countries in our sample. These range from a low of 2.6 percent for Sweden to a high of 28 percent for Jamaica. As Krueger and Lindahl (2000) point out the social return to education can be higher or lower than the private return. The former is likely if higher levels of human capital engender technological progress not captured by the private return or reduction in social variables (e.g. crime or fertility rates) or "more informed political decisions." The latter is likely if education serves towards raising social status without raising productivity.

Table 2 reports our average estimate of the social return to human capital for each country along with its standard error (the returns are based on the model of column 6 of Table 1). Figure 7 shows the density function of the social rate of return.

Figure 8 shows the density function of the social rate of return for the model of column 8 in Table 1 where trade orientation is a determinant of the rate of return to human capital. The distribution or returns is bimodal with the left mode corresponding to closed economies. The social rate of return is highest for the high-income economies: the average rate or return for the twenty high-income economies in our sample is 4.2 percent for the model of column 6 and 5.0 for model 8. The variance of returns for model 8 is greater than that of the other models (see Figures 7 and 8). In fact a number of estimated returns for low and middle income economies are negative. It is also interesting that, for this model, the estimates of the social rate of return to human capital for all but one of the six South East Asian economies (Indonesia, Korea, Malaysia, Singapore and Thailand) are among the highest of all economies in our sample. These countries have been praised incessantly for their outward orientation and for their efforts in providing widespread access to education opportunities for their population. The sole exception is Philippines a country notorious among the South East Asian economies for rent seeking and other unproductive activities.[10] Other

[10] Indonesia and the Philippines are ranked as the two most corrupt economies of those in our sample according to the Corruption Perceptions Index of Transparency International (2001) during the 1980-85 period. The Indonesian economy, however, is classified as open

outward oriented economies (e.g. Mauritius) also have high and significant estimates of the social rate of return to human capital.

In conclusion, we find that the social return to human capital is zero for most low-income economies and is highest for high-income economies (with the middle-income economies roughly between the two groups). As several researchers have pointed out (e.g. Psacharopoulos, 1994), private returns to education are higher for developing economies. Putting these together, our results indicate that positive externalities to the accumulation of human capital most likely have accrued to the industrial nations, while low income nations are likely to have experienced either no externalities or in some cases negative externalities.

4 Conclusion

This paper looks at the impact of human capital accumulation on the growth of output. It argues that previous studies have been unable to discern a significant effect because they assume that the contribution of the 'traditional' inputs (labor and physical capital) as well as human capital is constant both across countries and time. We examine both assumptions. First, we use data on the contribution of labor and physical capital that vary across countries and time to remove the effects of the growth of traditional inputs from output growth. Second, we show that the (growth of the) resulting TFP index depends on the growth of human capital. Importantly, we allow the contribution of human capital to TFP growth to vary across countries and time by modelling this contribution by a general function that we estimate via

by the Sachs/Warner criterion while the Philippines is considered to be closed for all the years of our sample, a factor that helps explain the difference in estimates.

semiparametric techniques.

Our analysis yields several conclusions. First, our semiparametric methodology enables us to recover estimates of the elasticity of human capital with respect to output that differ across countries and time. The average output elasticity varies substantially across countries and is, in general, positive for the high income economies though for low income economies it tends to be low and in some cases zero. This result provides empirical support to the hitherto unexplored proposition that human capital accumulation might not yield a beneficial effect on output. We also find that, *ceteris paribus*, the human capital elasticity of aggregate output is higher for outward-looking economies. Finally, we compute social rates of return to human capital from aggregate data. There is a wide dispersion of estimates. Our study is an important first step in deriving elasticities and rates of return to human capital based on aggregate (national) data in contrast to the preponderance of private rates of return from Mincerian earnings functions.

Appendix

Our sample consists of 51 countries during 1971-87 or a total of 867 observations. All variables are calculated for each country and time period so subscripts are omitted.

Output: Output in constant (1987) domestic prices (Y_c) is from the Nehru *et al.* (1995) data base; the price of output (q_Y) is the GDP deflator (from the *World Tables* of the World Bank). Output in constant 1987 US dollars (Y) is Y_C divided by the base year PPP (PPP_Y^0, from the Summers-Heston data base). The corresponding price index is defined as $P_Y = q_Y$ PPP_Y^0.

Output Share of Labor: We compute the share of labor in GDP (s_{YL}) first by collecting data on the compensation of employees paid by resident producers (as percent of GDP) from various issues of the *National Accounts Statistics* of the United Nations (Table 1.3). This data, however, do not account for self employment, a fact also pointed out by Gollin (1998). Therefore, we also obtain data on the number of self employed (employers and own account workers) in each country as a proportion of the number of employees and used these to adjust the UN data accordingly. This adjustment assumes implicitly that the average wage of employees and self employed workers is the same, an assumption also made by Gollin (1998). Data on the number of employees and self employed are from various issues of the *Year Book of Labour Statistics* of the International Labour Organization (ILO). Because complete data on the number of employees and self employed are not available for all countries some interpolation was necessary.

Labor: We estimate total labor compensation by multiplying s_{YL} by $q_Y Y_C$. We construct a price index of labor (q_L) by dividing labor compensation by the number of workers ($\aleph$, from the Summers-Heston data base) and normalizing this number to equal 1 in 1987 (base year). Labor quantity in constant domestic prices (L_C) is constructed implicitly by dividing labor compensation by q_L. Labor in constant 1987 US dollars (L) is L_C divided by the base year PPP for labor (PPP_L^0). The corresponding labor price index is defined as $P_L = q_L \ PPP_L^0$. The PPP for labor of country i is constructed by dividing the labor cost per worker at the base year by the corresponding value in the US, i.e. $PPP_L^0 = (q_L^0 L_C^0/\aleph^0)^i \,/\, (q_L^0 L_C^0/\aleph^0)^{US}$.

Physical Capital: Physical capital in constant (1987) domestic prices (K_C) is from the Nehru *et al.* (1995) data base; it is built from investment series (from the World Bank data base) via the perpetual inventory method. The acquisition price of investment (q_I) is the investment deflator (from the *World Tables* of the World Bank). There are no cross country data on the rental price of capital. Therefore, we constructed these in three ways. First, we assume that the value of labor and capital exhaust total output and the rental price of capital is $q_K = (q_Y Y_C - q_L L_C)/K_C$. Second, $q_K = q_I[r-(\widehat{q}_I)+\delta]$, where r is the rate of return to capital, $(\widehat{q}_I)$ is capital gains and δ is the depreciation rate. We assume the real return to capital $r-(\widehat{q}_I)$ differs between low, middle and high income countries. Following representative estimates reported by Harberger (1998) we set this rate equal to 9% for low income, 5% for middle income and 2% for high income countries. The rate of depreciation is that used by Nehru *et al.* (1995); it is 4% for all countries. Finally, we assume a constant real return to capital of 6%. This is close to the average for all the countries in Harberger (1998) and also to the average real long-term government bond yield for the countries with available data in our sample (data on long-term government bond yields are from the *International Financial Statistics* of the International Monetary

Fund). Physical capital in constant 1987 US dollars (K) is K_C divided by the base year PPP for investment (PPP_I^0, from the Summers-Heston data base). The corresponding capital price index is defined as $P_K = q_K \ PPP_I^0$. Finally, we define the cost share of capital $S_K = P_K K/C$ and labor $S_L = P_L L/C$ where $C = P_K K + P_L L$.

Human Capital: Our measure of the human capital stock is the total (primary, secondary and tertiary) number of years of schooling in the working age population; estimates are from the Nehru *et al.* (1995) data base.

Wage Rate for Raw Labor: We decomposed the share of labor in GDP (s_{YL}) into a component due to raw labor and one due to human capital. We accomplished this by assuming that human capital raises the (unknown) wage of raw labor (P_L^b) for country i as follows: $P_L^s = P_L^b e^{\rho H_s}$, where ρ is the return to schooling for country i and H_s is human capital (mean years of schooling) of country i for schooling level s. We consider four schooling levels: no schooling, primary, secondary and tertiary. The private rate of return to schooling for each country is from Bils and Klenow and is given in the final column of Table 1. For countries where Bils and Klenow provide no data, we use the average rate of return for different regions (Sub Saharan Africa, Asia, Latin America, North Africa/Middle East and OECD) from Psacharopoulos (1994). Human capital estimates by level of education for each country (H_s) are from the Nehru *et al.* (1995) data base. The human capital component in s_{YL} (as a percentage of s_{YL}) for country i is then obtained as $\sum_s \ell^s (P_L^s - P_L^b) / \sum_s \ell^s P_L^s$, where ℓ^s is country i's share of the working age population with level of education s. These shares (ℓ^s) are from the Barro-Lee data base. Pritchett (1996a) uses a similar procedure for identifying the human capital component of the total wage bill. Knowledge of the raw labor component of s_{YL} and the workforce is sufficient to calculate the wage rate for raw labor.

Political and Civil Freedom: We measure political and civil freedoms according to the index compiled by Freedom House (2000). The range of the index is from 1 to 7 with higher values indicating lower degrees of freedom. Freedom House defines political rights as those that "enable people to participate freely in the political process, which is the system by which the polity chooses authoritative policy makers and attempts to make binding decisions affecting the national, regional, or local community. In a free society, this represents the right of all adults to vote and compete for public office, and for elected representatives to have a decisive vote on public policies." They define civil liberties to "include the freedoms to develop views, institutions, and personal autonomy apart from the state." The Freedom House indexes are frequently used in empirical research (see Rodrik, 2000).

Outward Orientation: As Edwards (1998) discusses, measuring outward orientation is problematic. While a number of indices are available cross sectional for a limited number of countries, there is only one index available on a consistent basis for a cross section of countries across time. The Sachs and Warner (1995) binary index classifies a country as open (index equals one) according to four criteria: the extent of the black market premium, distortions created by export marketing boards, the ideological nature of the regime (socialist or otherwise) and quota coverage on imports of intermediate and capital goods. The other commonly used measure of trade openness that is available across countries and time, the ratio of exports (or imports) to GDP is a consequence of trade orientation rather than an independent indicator of openness. Moreover, the use of a binary indicator is in fact desirable since it allows us to present graphically differences in elasticities and rates of return between closed and open economies

Nehru *et al.* (1995) provide annual estimates of years of schooling for 1960-87 for 83 countries. The UN *National Accounts Statistics* do not provide consistent estimates of the compensation of employees (as percent of GDP) before 1970. In addition, the UN provides data for only 51 countries in the Nehru *et al.* data base. These constraints limit our sample size to 51 countries during 1970-87 or a total of 867 observations of annual growth rates. Nehru *et al.* (1995) build their estimate of the stock of human capital from enrollment data using the perpetual inventory method. Thus, starting our sample in 1970 (instead of 1960) may provide a more accurate estimate. Moreover, most of the countries omitted from the Nehru *et al.* data base are ranked (by them) in categories 3 or 4, indicating that there were substantial gaps in enrollment data and these had to be extrapolated.

Table A1: DATA AVERAGES BY COUNTRY
(Percent, 1971-1987)

Country	*Output Share of Labor* (s_{YL})	*Growth of* *Output* ($\widehat{Y}$)	*Labor* ($\widehat{L}$)	*Physical Capital* ($\widehat{K}$)	*Human Capital* ($\widehat{H}$)	*Total Factor Productivity* ($\widehat{TFP}$)
Algeria	44.19	4.60	3.35	7.29	4.05	-1.01
Australia	62.32	3.13	2.14	3.98	1.23	0.30
Austria	62.22	2.67	0.81	4.58	0.01	0.44
Belgium	64.73	2.31	0.74	3.01	0.43	0.76
Canada	60.26	3.89	2.30	4.63	0.92	0.66
Colombia	49.53	4.47	2.55	4.71	2.93	0.83
Costa Rica	54.83	3.89	3.56	6.29	2.02	-0.87
Denmark	61.98	2.30	0.98	3.39	0.67	0.40
Ecuador	43.03	5.71	2.71	5.60	2.54	1.44
El Salvador	49.03	1.54	1.90	4.69	2.75	-1.76
Ethiopia	64.61	2.51	2.17	4.91	7.42	-0.78
Finland	63.06	3.24	0.80	3.82	1.35	1.34
France	64.07	2.63	0.91	4.30	0.53	0.48
Germany	61.48	2.14	0.28	3.14	0.05	0.74
Greece	64.99	3.15	0.66	4.93	0.84	0.91
Iceland	59.25	5.12	2.27	4.79	1.52	1.83
India	69.58	3.82	1.99	4.51	3.33	1.07
Indonesia	73.22	6.15	2.23	10.41	3.30	1.70
Ireland	69.54	3.66	1.09	5.06	-1.21	1.38
Italy	65.44	2.97	0.52	3.62	0.98	1.41
Jamaica	72.76	-0.16	2.59	1.17	0.95	-2.29
Japan	65.06	4.06	0.87	7.37	0.24	0.86
Kenya	51.72	6.09	3.68	3.41	4.10	2.57
Korea	55.10	8.58	2.37	12.05	3.19	1.82
Madagascar	61.16	0.27	2.05	1.90	3.14	-1.74
Malawi	51.13	4.24	2.56	6.21	0.01	0.00
Malaysia	51.87	6.31	3.45	9.91	2.82	-0.22
Mauritius	48.92	5.51	2.25	3.15	1.80	2.80

Table A1 (cont'd): DATA AVERAGES BY COUNTRY

Country	*Output Share of Labor* (s_{YL})	*Growth of* *Output* ($\widehat{Y}$)	*Labor* ($\widehat{L}$)	*Physical Capital* ($\widehat{K}$)	*Human Capital* ($\widehat{H}$)	*Total Factor Productivity* ($\widehat{TFP}$)
Mexico	49.03	4.20	3.26	6.64	2.50	-0.70
Netherlands	62.98	2.15	1.41	3.21	0.27	0.08
New Zealand	60.47	2.25	1.71	3.26	1.77	-0.08
Norway	58.97	4.05	1.55	4.16	0.55	1.46
Pakistan	63.40	5.31	3.17	5.31	2.48	1.33
Panama	74.39	4.33	2.62	6.36	2.14	1.08
Paraguay	62.48	5.68	3.17	9.46	0.34	0.24
Philippines	58.47	3.43	2.49	6.31	1.87	-0.63
Portugal	63.34	3.52	1.51	4.79	1.54	0.72
Sierra Leone	45.63	1.39	1.57	2.38	5.23	-0.56
Singapore	43.90	7.42	3.08	12.37	3.64	-0.81
Spain	64.21	2.91	0.89	4.76	1.31	0.68
Sri Lanka	59.35	4.42	1.87	7.30	1.45	0.34
Sweden	66.23	1.96	0.85	2.95	0.67	0.40
Switzerland	66.42	1.42	0.55	3.52	0.59	-0.16
Tanzania	62.21	2.73	2.33	4.26	5.83	-0.02
Thailand	53.94	6.24	2.75	8.33	1.63	0.97
Turkey	42.53	5.19	2.06	6.35	3.09	0.84
U.K.	63.97	2.18	0.52	2.98	0.46	0.79
U.S.A.	65.78	2.80	1.86	2.89	0.47	0.59
Venezuela	52.25	1.87	4.08	4.55	3.44	-2.42
Zambia	62.87	1.21	3.03	0.54	4.94	-0.88
Zimbabwe	74.61	2.90	3.08	3.69	1.98	-0.40
Average	59.68	3.62	2.02	5.08	1.97	0.35
Std. Dev.	(9.86)	(3.78)	(1.22)	(3.25)	(1.75)	(3.31)

Note: See text for the calculation of Total Factor Productivity Growth, $\widehat{TFP}$.

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