Macroeconomic Dynamics, **15**, 2011, 595–615. Printed in the United States of America.
doi:10.1017/S1365100510000210

ARTICLES

THE EFFECT OF INFORMATION TECHNOLOGY AND HUMAN CAPITAL ON ECONOMIC GROWTH

ELENA KETTENI
University of Cyprus
and
Frederick University

THEOFANIS MAMUNEAS
University of Cyprus

THANASIS STENGOS
University of Guelph

In this paper we compare the impact of hardware, software, and communication equipment, widely referred to as information and communication technologies (ICT), on economic growth among the advanced industrialized countries. We use nonparametric techniques that allow us to estimate the output elasticities of ICT and human capital directly for each country and time period in our sample. Our results indicate that countries with high levels of ICT capital have high output elasticities of human capital. In addition, countries with high levels of human capital have high output elasticities of ICT, a result suggesting complementarity between the two.

Keywords: Information and Communication Technologies, Productivity, Human Capital, Semiparametric Smooth Coefficient Model

1. INTRODUCTION

In recent years, the rapid diffusion of information and communication technology (ICT) has attracted a lot of research. Even though substantial number of studies have examined in detail the effect of ICT investment on U.S. economic growth, only a handful have examined the relationship between productivity growth and ICT investment in other advanced economies. The purpose of this paper is to compare productivity performance and the impact of ICT investment on productivity and economic growth for a group of advanced industrialized economies.

Using detailed U.S. industry data, many recent studies have investigated the relationship between information technology (IT) capital and productivity growth, and have found that the impact of IT on U.S. productivity growth is quantitatively

We would like to thank the University of Cyprus research committee for financial support. Address correspondence to: Thanasis Stengos, Department of Economics, University of Guelph, Guelph, Ontario N1G 2W1, Canada; e-mail: tstengos@uoguelph.ca.

large and economically important [see, for instance, Barua and Lee (1997); Siegel (1997); Stiroh (1998, 2002); Feldstein (2003); Oliner and Sichel (2003); and Bosworth and Tripplet (2007)]. Some more recent studies have used individual cross-sectional country data to examine the effect of ICT on economic growth [for instance, (2002)-Basu et al. (2003); Hoon (2003); Colecchia and Schreyer (2002); and Jorgenson and Vu (2005)], and they found overall a positive and significant contribution of ICT to economic growth. Furthermore, Gordon (2004) suggested that the explanation of why Europe has been falling behind from the United States in terms of productivity growth lies in the ICT-intensive industries. Matteucci et al. (2005) and Timmer et al. (2007) showed that ICT has typically had a lower impact on productivity in Europe than in the United States, although there is a considerable variation within Europe. In addition, Van Ark et al. (2003) found that Canada also has been taking greater advantage than Europe of the possibilities offered by ICT to improve efficiency and productivity in many of its industries.

The contribution of our study is to go beyond what has been done so far in the literature and to compare the productivity performance and the impact of hardware, software, and communication equipment on productivity, and therefore economic growth, for the main group of the advanced industrialized countries (the OECD). As far as we know, there is no clear-cut evidence of the impact of ICT on productivity in these countries separately or as a group. Furthermore, we study the interaction and influence of ICT on the output elasticity of human capital and vice versa. The recent literature examining the effect of human capital on economic growth suggests that there exists a nonlinear relationship between human capital and economic growth [Galor and Zeira (1993); Durlauf and Johnson (1995); Kalaitzidakis et al. (2001); Durlauf et al. (2005); and Mamuneas et al. (2006)]. In addition, we want to examine whether ICT and human capital appear to be complements. Recent evidence [see, for instance, Bermand et al. (1994); Bermand et al. (1998); Falk and Stein (2001); Bresnahan et al. (2002); and Chun (2003)] suggests that ICT causes skill-biased technical change and therefore favors workers with higher educational attainments. Furthermore, Acemoglu (1998, 2001, 2002) argues that when it is more profitable to adopt skill-biased techniques, new technology will tend to be skill-biased. The twentieth century has been characterized by skill-biased technical change because the supply of skilled workers has grown steadily. This ability of skilled workers to deal with the introduction of new technologies results in an automatic increase in the demand for skills. Therefore, new technologies are more complementary to skilled workers than to unskilled ones. Following this literature, we observe an unresolved issue. Is technological progress skill-biased? Is it the case that the nature of the new technology complements skills (Acemoglu 1998), or is it merely the acceleration in the rate of technological progress and the changes in the technological environment that increases the demand for skilled workers in order to cope with a rapidly changing technological environment [Galor and Tsiddon (1997); Caselli (1999); Galor and Moav (2000)]? One of our main objectives is to establish the presence of possible interactions between ICT and human capital and attempt to partially address this question. This is the first study in the empirical growth literature as far as we know that attempts to do so.

We use nonparametric techniques to examine the impact of ICT capital on the process of productivity growth. The semiparametric smooth-coefficient model that we use allows us to estimate the output elasticity of ICT and human capital directly for each country and each time period. When the above methodology is applied to OECD data for the period 1980–2004, the results indicate a nonlinear relationship between ICT and productivity alongside a nonlinear relationship between human capital and productivity. In addition, our results indicate that at high levels of ICT capital, the output elasticities of human capital are larger and at high levels of human capital, measured by mean years of schooling, we obtain higher output elasticities of ICT capital. This finding seems to point to a complementary relationship between human capital and ICT. The rest of the paper is organized as follows. Section 2 discusses the methodology and the data sources, Section 3 presents the estimation results, and Section 4 concludes.

2. METHODOLOGY AND DATA SOURCES

2.1. Specification

We assume that technology can be represented by a general production function,

$$Y = F(P, E, H, I, t), \tag{1}$$

where Y is the total output, P is the total capital (including ICT capital), E is effective or human capital–augmented labor, H is the average human capital, I is the ICT capital, and t is a technology index measured by time trend. Total differentiation of (1) with respect to time and division by Y yields

$$\hat{Y} = \hat{A} + \varepsilon_P \hat{P} + \varepsilon_E \hat{E} + \varepsilon_H \hat{H} + \varepsilon_I \hat{I}, \tag{2}$$

where (ˆ) denotes a growth rate, $\hat{A} = (\partial F/\partial t)/Y$ is the exogenous rate of technological change, and $\varepsilon_i = \partial \ln Y/\partial \ln Q$ $(i = P, E, H, I)$ denotes output elasticity. The last two terms in equation (2) measure the externality effects on human capital and ICT capital accumulation, respectively. Equation (2), however, is not useful for empirical purposes because the growth rate of effective labor $\hat{E}$ is not observable and because we also want to estimate the total effect of ICT capital. The effective labor input is a function of the labor force, L, and average human capital, H, i.e., we have that $E = \Phi(L, H)$. Similarly, total capital is a function of physical capital (excluding ICT capital), K, and ICT capital, I; i.e., $P = \Psi(K, I)$. Thus we can decompose $\hat{E}$ and $\hat{P}$ as

$$\begin{aligned} \hat{E} &= \eta_L \hat{L} + \eta_H \hat{H} \\ \hat{P} &= \eta_K \hat{K} + \eta_I \hat{I}, \end{aligned} \tag{3}$$

where η_L and η_H are effective labor elasticities with respect to labor and average human capital, and η_K and η_I are total physical-capital elasticities with respect to

https://doi.org/10.1017/S1365100510000210 Published online by Cambridge University Press

non-ICT capital and ICT capital, respectively. Substituting (3) into (2), we have

$$\hat{Y} = \hat{A} + \alpha_L \hat{L} + \alpha_K \hat{K} + (\varepsilon_E \eta_H + \varepsilon_H)\hat{H} + (\varepsilon_P \eta_I + \varepsilon_I)\hat{I}. \tag{4}$$

The last two terms in parentheses in equation (4) measure the total effect of human capital and ICT capital, respectively, whereas the output elasticities of raw labor and physical capital are given by $\alpha_L = \varepsilon_E \eta_L$ and $\alpha_K = \varepsilon_P \eta_K$.

With data available for the above variables, we can directly estimate the elasticities using panel or cross-sectional data methods. However, this is not the case for the output elasticity with respect to ICT capital or human capital. Because we want to examine simultaneously the relationships between ICT capital and productivity, and human capital and productivity, we follow an alternative specification. The approach that we follow here is an extension of that of Mamuneas et al. (2006), who considered only the relationship between human capital and productivity. First, we construct a Total Factor Productivity (TFP) index based only on labor and non-ICT capital. This index allows the contribution of each input to differ and to be dictated by the data. We define the Tornqvist index of TFP growth for country i in year t as

$$\hat{\mathrm{TFP}}_{it} = \hat{Y}_{it} - w_{Lit}\hat{L}_{it} - w_{Kit}\hat{K}_{it},$$

where $w_{lit} = 0.5(s_{lit} + s_{lit-1})(l = L, K)$ are the weighted average cost shares of labor and non-ICT capital and $\hat{Q}_{it} = \ln Q_{it} - \ln Q_{it-1}, (Q = Y, L, K)$.[1] This measure of TFP contains the components of output growth that cannot be explained by the growth of the inputs (K, L) in equation (4). Diewert (1976) suggested that this index is an exact index of technological change for a general translog production function, under certain conditions. However, this index in our case will be biased and will depend on the effect of ICT and human capital. Using this definition of TFP along with equation (4), while taking a discrete approximation of the continuous growth rates, we obtain

$$\begin{aligned} \hat{\mathrm{TFP}}_{it} = \hat{A}_{it} &+ \left[(\alpha_{Lit} - w_{Lit})\hat{L}_{it} + (\alpha_{Kit} - w_{Kit})\hat{K}_{it}\right] \\ &+ (\varepsilon_E \eta_H + \varepsilon_H)\hat{H}_{it} + (\varepsilon_{Pit}\eta_{Iit} + \varepsilon_{Iit})\hat{I}_{it}, \end{aligned} \tag{5}$$

where $\hat{A}_{it}$ is the exogenous technical change of the ith country at time t, and the term in brackets is the scale effect, which is measured as the deviation of the output elasticities from the observed cost shares. The two last terms in parentheses present the total contributions of human capital and ICT, respectively. This contributions are made up of two components: the first is the direct effect of human capital or ICT capital and the second is the indirect or externality effect.

In this study we evaluate the last two terms in equation (5), which capture the contributions of human capital and ICT capital to TFP growth using a local linear nonparametric methodology.[2] That is, we will model the contribution of ICT capital to aggregate production as a general unknown function $\theta_I(.)\hat{I}_{it}$. Similarly, because we want to study the interaction and influence of ICT on the returns of human capital and growth, following results from the recent empirical growth literature of the effect of human capital on economic growth [see Kalaitzidakis et al. (2001)], we also allow the contribution of human capital to be possibly nonlinear as $\theta_H(.)\hat{H}_{it}$. In addition, standard cost minimization with respect to physical capital and labor implies that

$$\alpha_{lit} = \rho w_{lit}, \quad l = K, L, \tag{6}$$

where ρ is the elasticity of returns to scale of capital and labor. Using equation (6) and the unknown functions mentioned above, equation (5) becomes

$$\begin{aligned}\widehat{\text{TFP}}_{it} &= \hat{A}_{it} + (\rho - 1)(w_{Kit}\hat{K}_{it} + w_{Lit}\hat{L}_{it}) + \theta_I(.)\widehat{I}_{it} + \theta_H(.)\widehat{H}_{it} \\ &= \widehat{A}_{it} + \alpha\widehat{M}_{it} + \theta_I(.)\widehat{I}_{it} + \theta_H(.)\widehat{H}_{it},\end{aligned} \tag{7}$$

where $\widehat{M}_{it} = w_{Kit}\hat{K}_{it} + w_{Lit}\hat{L}_{it}$ and $a = (\rho - 1)$. Semiparametric estimation of the above equation allows ICT-capital accumulation, and human capital also, to influence TFP growth in a nonlinear fashion.

In the above equation, $\hat{A}_{it}$ can be considered 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 procyclical behavior of TFP growth. With regard to the unknown functions θ_s ($s = I, H$), we assume that they depend both on the level of ICT capital and on the stock of human capital. The equation of interest now becomes

$$\hat{\text{TFP}}_{it} = \alpha_0 + \sum_{i=1}^{N-1}\alpha_i D_i + \sum_{t=1}^{T-1}\alpha_t D_t + \alpha\widehat{M}_{it} + \theta_I(.)\hat{I}_{it} + \theta_H(.)\hat{H}_{it} + u_{it}.$$

If we let $W_{it}^T = (D_i, D_t, \widehat{M}_{it})$ and $V_{it} = \{I_{it}, H_{it}\}$, the model can be written more compactly as

$$\hat{\text{TFP}}_{it} = W_{it}^T\beta + \theta_I(V_{it})\hat{I}_{it} + \theta_H(V_{it})\hat{H}_{it} + u_{it}. \tag{8}$$

For proper estimation we assume that $E(u_{it} \mid W_{it}, V_{it}, \hat{I}_{it}, \hat{H}_{it}) = 0$. Below we describe the estimation method that we will apply.

2.2. Econometric Estimation: A Semiparametric Smooth-Coefficient Approach

A semiparametric smooth-coefficient model is considered to be a useful and flexible specification for a general regression relationship with varying coefficients. It is a generalization of varying-coefficient models and it is based on polynomial regression [see, for instance, Fan (1992), Fan and Zhang (1999), Li et al. (2002), Kourtellos (2003), and Mamuneas et al. (2006)]. A semiparametric varying-coefficient model imposes no assumption on the functional form of the coefficients, and the coefficients are allowed to vary as smooth functions of other variables. Specifically, varying-coefficient models are linear in the regressors, but their coefficients are allowed to change smoothly with the values of other variables. One way of estimating the coefficient functions is using a local least-squares method with a kernel-weighting function. A general semiparametric smooth-coefficient model is given by

$$y_i = \alpha(z_i) + x_i'\beta(z_i) + u_i, \tag{9}$$

where y_i denotes the dependent variable, x_i denotes a $p \times 1$ vector of variables of interest, z_i denotes a $q \times 1$ vector of other exogenous variables, and $\beta(z_i)$ is a vector of unspecified smooth functions of z_i. Based on Li et al. (2001), the above semiparametric model has the advantage that it allows more flexibility in functional form than a parametric linear model or a semiparametric partially linear specification. Furthermore, the sample size needed to obtain reliable semiparametric estimates need not be as large as that required for estimating a fully nonparametric model. It should be noted that when the dimension of z_i is greater than one, this model also suffers from the "curse of dimensionality," although to a lesser extent than a purely nonparametric model where both z_i and x_i enter nonparametrically. Fan and Zhang (1999) suggest that the appeal of the varying-coefficient model is that allowing coefficients to depend on other variables can significantly reduce the modeling bias and avoid the curse of dimensionality. Equation (9) can be rewritten as

$$\begin{aligned} y_i &= \alpha(z_i) + x_i^T\beta(z_i) + \varepsilon_i = \left(1, x_i^T\right)\begin{bmatrix}\alpha(z_i)\\ \beta(z_i)\end{bmatrix} + \varepsilon_i \\ y_i &= X_i^T\delta(z_i) + \varepsilon_i, \end{aligned} \tag{10}$$

where $\delta(z_i) = (\alpha(z_i), \beta(z_i)^T)^T$ is a smooth but unknown function of z. One can estimate $\delta(z)$ using a local least-squares approach, where

$$\begin{aligned} \widehat{\delta}(z) &= \left[(nh^q)^{-1}\sum_{j=1}^{n} X_j X_j^T K\left(\frac{z_j - z}{h}\right)\right]^{-1}\left[(nh^q)^{-1}\sum_{j=1}^{n} X_j y_j K\left(\frac{z_j - z}{h}\right)\right] \\ &= [D_n(z)]^{-1}A_n(z), \end{aligned}$$

$D_n(z) = (nh^q)^{-1}\sum_{j=1}^{n} X_j X_j^T K[(z_j - z)/h]$, $A_n(z) = (nh^q)^{-1}\sum_{j=1}^{n} X_j y_j K[(z_j - z)/h]$. $K(.)$ is a kernel function, and $h = h_n$ is the smoothing parameter for sample size n.The intuition behind the above local least-squares estimator is straightforward. Let us assume that z is a scalar and $K(.)$ is a uniform kernel. In this case the expression for $\widehat{\delta}(z)$ becomes

$$\widehat{\delta}(z) = \left(\sum_{|z_j - z|\le h} X_j X_j^T\right)^{-1}\sum_{|z_j - z|\le h} X_j y_j.$$

In this case $\widehat{\delta}(z)$ is simply a least-squares estimator obtained by regressing y_j on X_j using the observations of (X_j, y_j) that their corresponding z_j is close to z $(|z_j - z| \leq h)$. Because $\delta(z)$ is a smooth function of z, $|\delta(z_j) - \delta(z)|$ is small when $|z_j - z|$ is small. The condition that nh^q is large ensures that we have sufficient observations within the interval $|z_j - z| \leq h$ when $\delta(z_j)$ is close to $\delta(z)$. Therefore, under the conditions that $h \to 0$ and $nh^q \to \infty$, one can show that the local least-squares regression of y_j on X_j provides a consistent estimate of $\delta(z)$. In general, it can be shown that

$$\sqrt{nh^q}[\widehat{\delta}(z) - \delta(z)] \to N(0, \Omega),$$

where Ω can be consistently estimated. The estimate of Ω can be used to construct confidence bands for $\widehat{\delta}(z)$. We use a standard multivariate kernel density estimator with Gaussian kernel and cross validation to choose the bandwidth.

2.3. Data Sources

To implement the model empirically, we obtain data on output, labor, and non-ICT and ICT capital stocks from the OECD database.[3] The human capital stock data are obtained and updated from Vikram and Dhareshwar (1993). The countries included in the analysis are Austria, Belgium, Denmark, Finland, France, Germany, Greece, Ireland, Italy, the Netherlands, Portugal, Spain, Sweden, the United Kingdom, and the United States for the period from 1980 to 2004. The sample of countries in the analysis is chosen based on the availability of data on ICT and human capital. In addition these countries, for this time period, have experience a rapid expansion of ICT capital investment.

The output is the gross domestic product (GDP) in constant 2000 euro prices. The price of output is calculated as the value of current GDP divided by the GDP in constant prices. The labor input is defined in terms of man-hours. The quantity of labor is constructed by dividing the labor cost by the labor price index. The labor price is obtained by dividing labor costs with total employment times average hours worked by the employees per year, and normalized to be 1 in 2000. Both output and labor quantities were adjusted for purchasing power parity (PPP).

With respect to capital, we define two categories: non-ICT and ICT capital. The non-ICT capital includes non-ICT equipment, transportation equipment, and nonresidential structures, whereas ICT capital includes IT hardware, communication equipment, and software [for a detailed description of the data see Pilat and Schreyer (2004)]. The capital inputs are defined as the stock of capital in constant 2000 euro prices and are calculated by dividing the ICT and non-ICT capital stocks in current prices, obtained from the OECD database, by their corresponding price index. A Tornqvist price index of non-ICT capital is constructed by using the investment price deflator of non-ICT equipment, transportation equipment, and nonresidential structures. Similarly, the price index of ICT capital stock is constructed by using the investment price deflators of IT hardware, communication

TABLE 1. Descriptive statistics: Mean values, 1980–2004

Country	Growth rate of TFP $\hat{\text{TFP}}_{it}$	Growth rate of ICT capital $\hat{I}_{it}$	Growth rate of Human capital $\hat{H}_{it}$	Level of ICT[a] capital I_{it}	Level of Human[b] capital H_{it}
Austria	0.0113	0.117	−0.0003	3,804.8	8.61
Belgium	0.0141	0.141	0.0029	5,497.1	8.32
Denmark	0.0116	0.146	0.0053	3,315.3	9.29
Finland	0.0192	0.154	0.0119	2,862.4	10.61
France	0.0102	0.132	0.0014	18,754.7	8.31
Germany	0.0139	0.105	−0.0026	35,737.6	8.03
Greece	0.0095	0.149	0.0095	1,869.1	9.34
Ireland	0.0191	0.202	−0.0111	1,126.9	11.81
Italy	0.0029	0.172	0.0072	26,064.9	8.01
Netherlands	0.0099	0.129	0.0016	5,695.7	8.32
Portugal	0.0121	0.171	0.0146	2,191.8	6.08
Spain	0.0062	0.168	0.0092	10,800.5	7.25
Sweden	0.0139	0.152	0.0038	5,879.2	9.86
UK	0.0178	0.187	0.0013	28,485.2	9.91
USA	0.0146	0.146	0.0033	268,575	11.55

[a]Millions of 2000 euros.
[b]Mean years of education.

equipment, and software. The capital stocks in constant prices were adjusted for PPP.

The human capital stock data are obtained from Vikram and Dhareshwar (1993). For a full description of their methodology see Vikram et al. (1995). This data set covers the period from 1950 to 1990 and human capital stock is defined as total mean years of education. We use extrapolation to update the human capital stock to 2004. For the update of the data we also take into consideration the human capital stock constructed by Barro and Lee (2001). However, we cannot directly use the Barro and Lee data for our analysis because their human capital data are calculated at five-year intervals. We are aware that the extrapolation method may not be the most appropriate, but we are confident that the results obtained using the updated series would be fairly robust, as the human capital stock for each country, measured as mean years of education, does not change much throughout the years. We are also aware that human capital includes besides years of education, job experience as well. Because we were unable to find measures that take into account both education and experience, we are forced to use only data from available sources. These data have also been used in previous studies and that allows a direct comparison of our results with theirs.

Table 1 presents the mean of the growth rates of TFP of ICT and human capital, along with the levels of ICT and human capital for each country in our sample. The

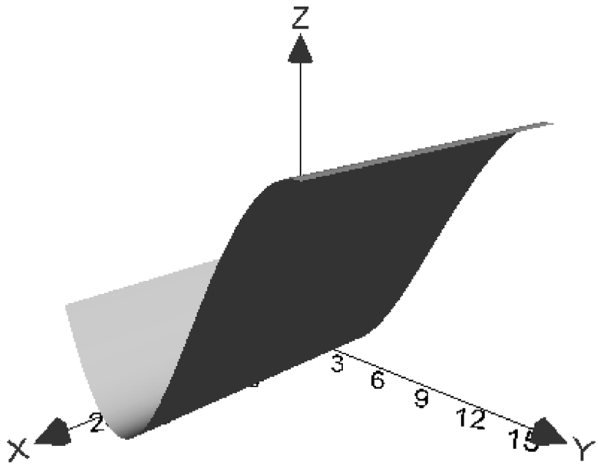

FIGURE 1. Output elasticities of ICT capital, where $X =$ ICT capital, $Y =$ human capital, and $Z = \theta_I(I_{it}, H_{it})$.

TFP growth rates are constructed by subtracting from the growth rate of output the growth rates of labor and non-ICT capital weighted by their cost shares. On the average, countries with the highest TFP growth rates also have high levels (or growth rates) of ICT and human capital.

3. EMPIRICAL FINDINGS

The semiparametric smooth-coefficient model that we estimate is given below:

$$\hat{\mathrm{TFP}}_{it} = \alpha_0 + \sum_{i=1}^{N-1} \alpha_i D_i + \sum_{t=1}^{T-1} \alpha_t D_t + \alpha \widehat{M}_{it} + \theta_I(.)\hat{I}_{it} + \theta_H(.)\hat{H}_{it} + u_{it}.$$

A standard multivariate kernel density estimator with Gaussian kernel is employed and the bandwidth is chosen using cross validation. When estimating the semiparametric smooth-coefficient model, we obtain estimates of $\theta_s(I_{it}, H_{it}.)$, $s = I, H$, the output elasticities of ICT and human capital, respectively, along with estimates for the coefficients of the linear part of the model. From the linear part the parameter a_0 is positive and significant, whereas the parameter a capturing the scale effect is insignificant, a result suggesting that constant returns to scale cannot be rejected. In addition, we performed tests for the joint significance of the dummy coefficients. The results from these tests suggest that the dummy variables should be included in the model and therefore the exogenous technological change varies across countries and time.[4]

The output elasticities of ICT and human capital are presented graphically in Figures 1 and 2, respectively, as three-dimensional functions. The graphs clearly indicate that these functions are nonlinear. We also produce a two-dimensional

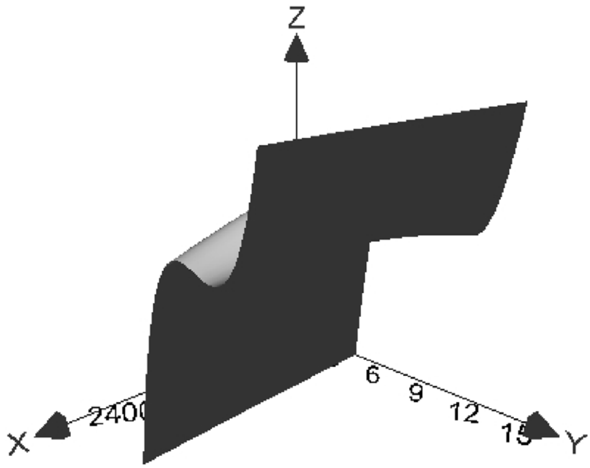

FIGURE 2. Output elasticity of human capital, where $X = $ ICT capital, $Y = $ human capital, and $Z = \theta_H(I_{it}, H_{it})$.

graph of the semiparametric coefficients, evaluating the θ_s functions at the median[5] of one of the two variables. In the graphical analysis that follows, in Figures 3 and 4, we have plotted the estimated θ_s along with their 95% confidence bands.[6] In figure 3, the output elasticity of ICT capital, $\theta_I(I_{it}, \overline{H})$, is plotted against the ICT capital evaluated at the median of human capital. This graph indicates that the output elasticities of ICT initially decline and then start increasing above a certain level of ICT capital. In all sample points, ICT has a positive effect on

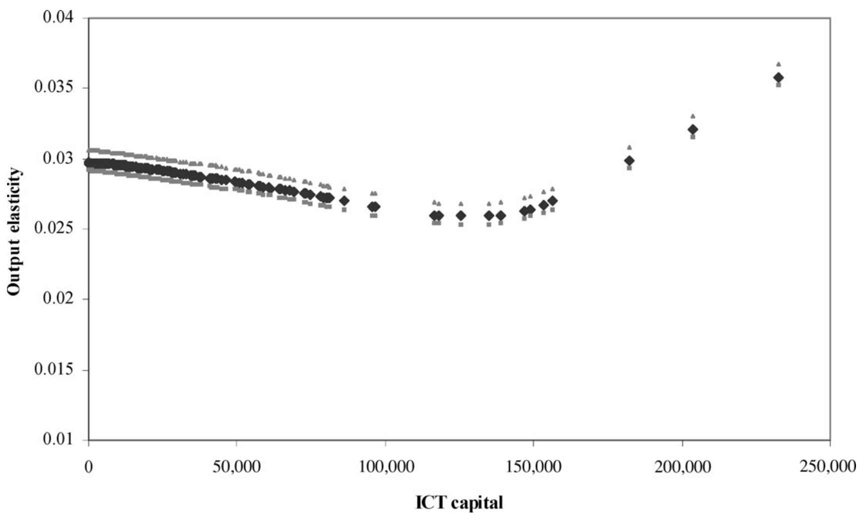

FIGURE 3. Output elasticity of ICT capital, $\theta_I(I_{it}, \bar{H})$, holding human capital at the median.

https://doi.org/10.1017/S1365100510000210 Published online by Cambridge University Press

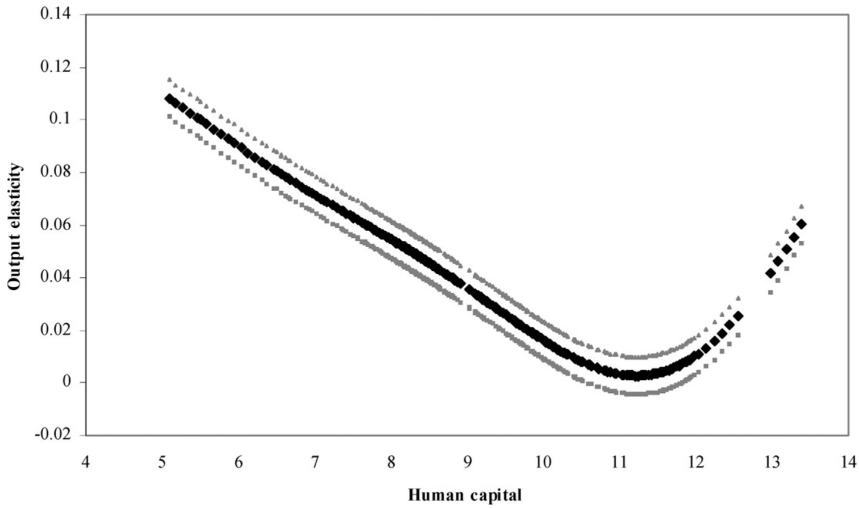

FIGURE 4. Output elasticity of human capital, $\theta_H(\bar{I}, H_{it})$, holding ICT capital at the median.

productivity, an effect that depends on the level of ICT and human capital in each country under investigation. Ketteni (2009) also obtains a nonlinear relationship of output elasticity of ICT capital for a number of U.S. industries, using a similar methodology.

In Figure 4 the output elasticity of human capital, $\theta_H(\overline{I}, H_{it})$, is plotted against the level of human capital evaluated at the median of ICT capital. Figure 4 clearly suggests that there is a nonlinear relationship between human capital and productivity and therefore growth.[7] This result confirms recent findings from the empirical growth literature [see Kalaitzidakis et al. (2001) and Mamuneas et al. (2006)], which estimated a nonlinear relationship between human capital and growth. In light of the limited country-specific evidence regarding the interactions between different types of labor and ICT, we find that a nonlinear relationship between human capital and growth still persists in the presence of ICT effects. Furthermore, the graph that is obtained is very similar to the one in Mamuneas et al. (2006).

The above figures indicate that the output elasticities of ICT and human capital vary considerably among countries and years, even though the output elasticities of human capital have larger variation. These results show that all countries in our sample benefit from investing in ICT and human capital. In Table 2 we report the mean values of output elasticity for each country in our sample. The output elasticities of ICT capital vary between 0.02365 (Portugal) and 0.03767 (the United States). The United States has the largest output elasticity of ICT, followed by Ireland, Finland, the United Kingdom, and Sweden. These countries appear to be the top five countries with respect to output growth rates and productivity or levels (and growth rates) of ICT and human capital. Furthermore, some of them

TABLE 2. Output elasticities: Mean values and standard errors, 1980–2004

Country	Output elasticity of ICT capital $\theta_I(I_{it}, H_{it})$	Output elasticity of Human capital $\theta_H(I_{it}, H_{it})$
Austria	0.02881	0.0351
	0.0002	0.0008
Belgium	0.02813	0.0385
	0.0007	0.0008
Denmark	0.03037	0.0275
	0.0011	0.0104
Finland	0.03348	0.0195
	0.0070	0.0330
France	0.02806	0.0385
	0.0004	0.0002
Germany	0.02736	0.0418
	0.0004	0.0035
Greece	0.03055	0.0277
	0.0041	0.0130
Ireland	0.03582	0.0198
	0.0037	0.0613
Italy	0.02739	0.0422
	0.0014	0.0019
Netherlands	0.02813	0.0385
	0.0004	0.0003
Portugal	0.02365	0.0669
	0.0010	0.0312
Spain	0.02581	0.0517
	0.0003	0.0096
Sweden	0.03170	0.0220
	0.0021	0.0022
UK	0.03187	0.0218
	0.0006	0.0056
USA	0.03767	0.0253
	0.0115	0.0119

also have the highest TFP growth rates. These results are consistent with those of Matteucci et al. (2005), who compare Germany, Italy, the United Kingdom, and the United States and find that the U.K. experience with ICT was closer to the U.S. experience.

The average output elasticities of human capital by country (see the second column of Table 2) vary from 0.0195 to 0.0669. Portugal appears to have the largest elasticity of human capital, followed by Spain, Italy, and Germany. These countries appear to have lower levels of human capital but high growth rates of both ICT and human capital. As both ICT and human capital increase, this causes the output elasticity of human capital to increase. From Table 2, we observe that some countries that already have high levels of ICT and human capital also have higher output elasticities of ICT capital, whereas countries with high growth rates of ICT and human capital have higher output elasticities of human capital. In order for one country to have high output elasticities of ICT and human capital, and therefore a larger effect on growth, it must have either high levels of ICT and human capital or a high growth rate for these capital stocks.

To ensure the robustness of our results, we performed some further tests. We have tested for endogeneity to check whether an IV approach will be more appropriate. Using lagged values as instruments, we obtain a bootstrapped Hausman-type test for endogeneity with a p-value of 0.6123 based on 199 bootstraps. Therefore the null hypothesis of no endogeneity cannot be rejected. The test is described in the Appendix. We also tested the null hypothesis of the smooth-coefficient model against a fully nonparametric alternative. This test was performed using the residuals from the smooth coefficient model as the null model, and it is a variant of the Fan and Li (1996) specification test. We also present a description of the test in the Appendix. We obtained a bootstrapped p-value of 0.3571 for this test based on 199 bootstraps, and hence the null of the smooth-coefficient semiparametric model cannot be rejected. We have also estimated the model by parameterizing the nonlinear part of the model using third-power polynomials (based on the graphs) in the ICT and human capital. Based on asymptotic F-tests we cannot reject the hypothesis that the effects of ICT and human capital follow a third-power polynomial with p-values for the significance of the polynomial terms of 0.0134 and 0.0234, respectively. Therefore, the use of a smooth-coefficient semiparametric model is justified. Finally, in order to take into account the size of each country, we have reestimated the smooth-coefficient model using ICT capital in per capita terms. Both models yield similar results.[8]

The recent literature [Bermand et al. (1998); Falk and Stein (2001); Chun (2003)] suggests that ICT capital causes skill-biased technical change, and therefore favors skilled/more educated workers, who are substitutes for unskilled ones. One of our objectives in this paper is to examine possible interactions between ICT and human capital, in order to ascertain the degree to which these two types of capital are complements. For instance, if human capital and ICT capital are complements for the same level of human capital, one would expect the output elasticity of human capital (marginal product) to increase as the ICT capital increases. To do so, we perform two different experiments. In the first, we evaluate the output elasticities of human and ICT capital at the first, second, and third quartiles of one of the two variables. In Figure 5 we present the graph of the output elasticity of human capital evaluated at three different levels of ICT capital, $\theta_H(I_L, H_{it})$, $\theta_H(\overline{I}, H_{it})$, and $\theta_H(I_H, H_{it})$, where I_L is the value of ICT capital in the first quartile (low level of ICT capital) and I_H is the value in the third quartile (high level of ICT capital). In this way, we can observe what happens to the output elasticity of human capital when the level of ICT changes. Similarly we

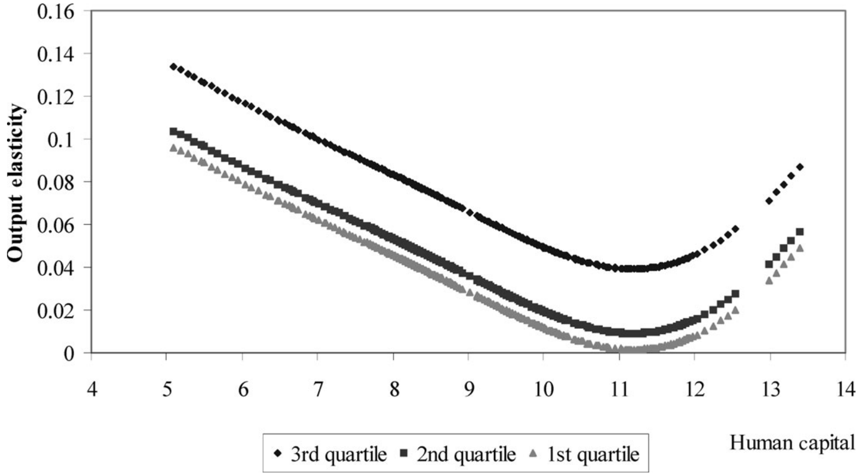

FIGURE 5. Output elasticities of human capital (different levels of ICT capital).

have estimated the output elasticity of ICT capital, $\theta_I(I_{it}, H_{it})$, for three different levels of human capital (low, mean, and high), and they are presented in Figure 6. The two figures indicate a consistent complementary relationship between human capital and ICT capital.

Furthermore, to capture the effect of human capital on the output elasticity of ICT, we plot $\theta_I(\bar{I}, H_{it})$, that is, the output elasticity of ICT evaluated at the median of ICT capital. In this way we can observe how the output elasticities of ICT, at the median, change with the level of human capital. The output elasticities

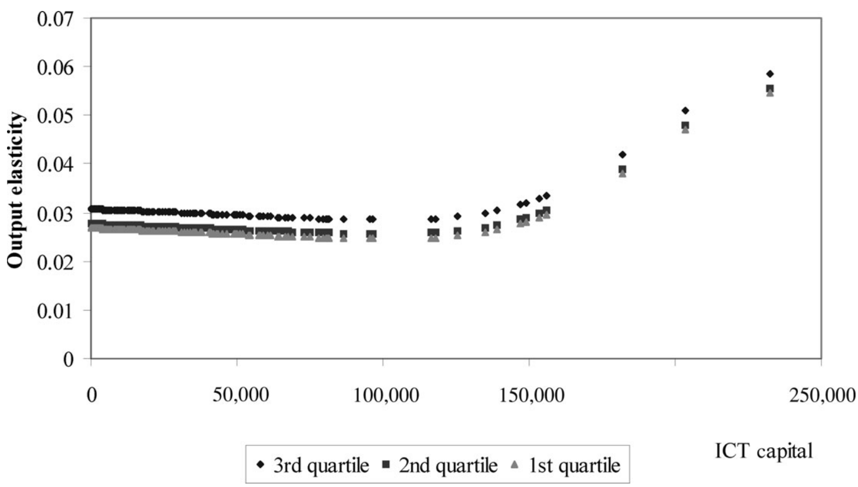

FIGURE 6. Output elasticities of ICT capital (different levels of human capital).

https://doi.org/10.1017/S1365100510000210 Published online by Cambridge University Press

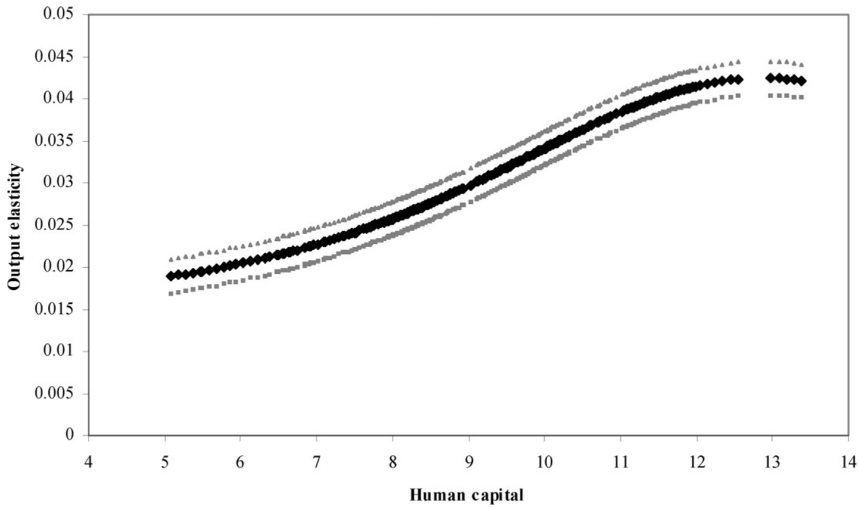

FIGURE 7. Output elasticity of ICT capital, $\theta_I(\bar{I}, H_{it})$, holding ICT at the median.

estimated are presented in Figure 7. Figure 7 indicates that the output elasticities of ICT increase with the level of human capital. That is, at higher levels of human capital stock, measured by mean years of schooling, we observe higher output elasticities of ICT. This could be due to the fact that in countries with high levels of ICT capital there is a greater need for more educated workers in order to cope with new technologies, whereas this is not the case in countries with low levels of ICT. Similarly, to check if the presence of ICT affects the output elasticities of human capital, we plot $\theta_H(I_{it}, \bar{H})$. These output elasticities of human capital are presented in Figure 8. Figure 8 shows how the median output elasticities of human capital change with ICT investment. From Figure 8 we observe that at high levels of ICT capital, the output elasticities of human capital are higher. The output elasticities of human capital increase with the level of ICT capital.

To conclude, both ICT and human capital have a nonlinear relationship with productivity and therefore economic growth. In addition, there exist interactions between the two variables, because in countries with high levels of ICT capital we obtain higher output elasticities of human capital and in countries with more educated workers the output elasticities of ICT capital are higher. Therefore, with regard to the question in the literature of whether technological progress is skill-biased, we can merely say that the two types of capital appear to have a positive correlation and to be complementary. Therefore, in countries with high levels of ICT, the need for more skilled and educated workers to cope with the new technologies is higher, but also if countries have high levels of human capital, then technologies complementary to these workers are likely to be developed. Both types of capital are needed, though, to get higher productivity and

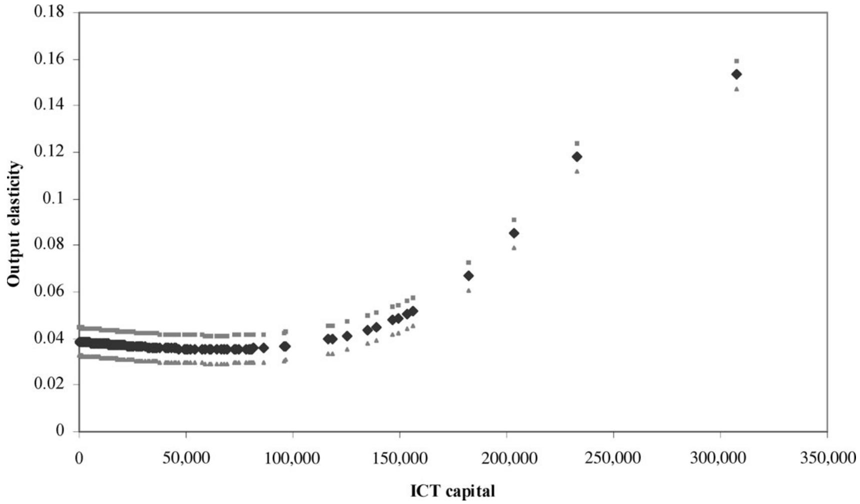

FIGURE 8. Output elasticity of human capital, $\theta_H(I_{it}, \bar{H})$, holding human capital at the median.

therefore growth. We cannot say more as to whether the nature of new technologies or their acceleration causes skill-biased technical change, due to data limitations in distinguishing between different types of labor by skill. We can conclude, though, that a complementary relationship exists between the two types of capital.

4. CONCLUSION

In this paper, we compare the productivity performance and the impact of hardware, software, and communication equipment on economic growth among the advanced industrialized countries (OECD). We study the influence of ICT capital on growth by also allowing the presence of human capital captured by mean years of schooling to interact with ICT capital. We use nonparametric techniques to examine the impact of ICT and human capital on the process of productivity growth by allowing the contribution of various inputs (including human capital) as well as that of ICT and human capital to vary across countries and time. This is accomplished by constructing an index of TFP based on only nonhuman capital labor and non-ICT capital inputs and by using this index to evaluate the impact of ICT and human capital on TFP growth via semiparametric methods. The semiparametric smooth-coefficient model that we use allows us to estimate the elasticity of ICT and human capital directly for each country and time period. In addition, we examine the interaction between human capital and ICT capital to find the interrelationship between the two variables. Recent literature examining the effect of human capital on economic growth suggests a nonlinear relationship between human capital and growth. Here we confirm that this nonlinear relationship still persists in the presence of ICT effects. In addition, we find that the relationship between ICT capital and growth is nonlinear, a result consistent with the previous literature. Furthermore, we find that at high levels of ICT capital the output elasticities of human capital are higher and at high levels of human capital we get higher output elasticities of ICT, a result suggesting complementarity and a positive correlation between the two types of capital. Therefore, in countries with high levels of human capital, new ICT will be more productive, and in countries with high levels of ICT, highly educated labor is needed. We cannot establish whether the nature of new technologies or their acceleration causes skill-biased technical change, due to existing data limitations in distinguishing between different types of labor by skill. We can conclude, though, that a complementary relationship exists between the two types of capital. In light of limited country-specific evidence regarding interactions between different types of labor and ICT, we leave this question for future research.

NOTES

1. Given that labor costs should be the same, the cost shares of effective and traditional labor are the same independent of how we define labor.

2. Following the cross country literature [see Durlauf and Johnson (1995); Kourtellos (2003); Masanjah and Papageorgiou (2004)], parameter heterogeneity may exist, in the sense that the effect of a change in a particular variable on growth is not the same. Also, as Galor (2005) stated, it is the recognition that the growth process is characterized by different stages of development that leads to the observed nonlinearities in the data. Moreover, several researchers suggest that there are important differences in the way human capital affects growth [see Kalaitzidakis et al. (2001) and Mamuneas et al. (2006)]. Galor and Zeira (1993) suggest that credit constraints may limit the abiity of individuals to invest in human capital. Hence, inequality, in the presence of credit market imperfections, may be detrimental to human capital formation and economic development. In another paper, Ketteni et al. (2007) provide evidence in favor of a nonlinear relationship between initial income, human capital, and ICT capital, on the one hand, and growth, on the other.

3. All data are expressed in millions.

4. We have also estimated the model including only the country dummies and a trend variable. The estimated coefficient of the trend variable is 0.0041 and it is statistically significant. The results, however, do not change much.

5. The median is used to avoid possible asymmetries and outliers that would affect the results. We would like to thank the referee for bringing this issue to our attention.

6. We are using 199 bootsraps to construct the confidence bands.

7. For robustness purposes, we have also estimated the elasticities for the period up to 1990 (where the extrapolation began). Also, we have used Barro and Lee (1997), by expanding their five-year interval data, assuming a constant growth rate, to a complete annual series. The results in both cases are similar to the reported results in the paper and are available upon request.

8. The results are available from the authors upon request.

REFERENCES

Acemoglu, Daron (1998) Why do new technologies complement skills? Directed technical change and wage inequality. *Quarterly Journal of Economics* 113(4), 1055–1089.

Acemoglu, Daron (2001) Factor Prices and Technical Change: From Induced Innovations to Recent Debates. Department of Economics working paper 01-39, Massachusetts Institute of Technology.

Acemoglu, Daron (2002) Technical change, inequality and the labor market. *Journal of Economic Literature* 40(1), 7–72.

Barro, Robert J. and Jong-Wha Lee (2001) International Data on Educational Attainment: Updates and Implications. CID Working Paper 42.

Barua, Anitesh and Byungtae Lee (1997) The information technology productivity paradox revisited: A theoretical and empirical investigation in the manufacturing sector. *International Journal of Flexible Manufacturing Systems* 9, 145–166.

Basu, Susanto, John G. Fernald, Nicholas Oulton, and Srinivasan Sylana (2003) The Case of the Missing Productivity Growth: Or Does Information Technology Explain Why Productivity Accelerated in the US but Not the UK? NBER working paper 10010.

Bermand, Eli, John Bound, and Zvi Grilicliches (1994) Changes in the demand for skilled labor within U.S. manufacturing: Evidence from the Annual Survey of Manufacturers. *Quarterly Journal of Economics* 109(2), 367–397.

Bermand, Eli, John Bound, and Machin Stephen (1998) Implications of skill-biased technological change: International evidence. *Quarterly Journal of Economics* 113(4), 1245–1279.

Bosworth, Barry P. and Jack E. Tripplet (2007) The early 21st century US productivity expansion is still in services. *International Productivity Monitor* 14, 3–19.

Bresnahan, Timothy F., Erik Brynjolfosson, and Lorin M. Hitt (2002) Information technology, workplace organization and the demand for the skilled labor: Firm level evidence. *Quarterly Journal of Economics* 117(1), 404–437.

Cai, Z., M. Das, H. Xiong, and X. Wu (2006) Functional coefficient instrumental variable models. *Journal of Econometrics* 133, 207–241.

Caselli, Francesco (1999) Technological revolutions. *American Economic Review* 89(1), 78–102.

Chun, Hyunbae (2003) Information technology and demand for the educated workers: Disentangling the impacts of adoption versus use. *Review of Economic and Statistics* 83(1), 1–8.

Colecchia, Alessandra and Paul Schreyer (2002) ICT investment and economic growth in the 1990s: Is the United States a unique case? *Review of Economic Dynamics* 5, 408–442.

Diewert, W. Erwin (1976) Exact and superlative index numbers. *Journal of Econometrics* 4, 115–146.

Durlauf, Steven N. and Paul A. Johnson (1995) Multiple regimes and cross-country growth behavior. *Journal of Applied Econometrics* 10, 365–384.

Durlauf, Steven N., Paul Johnson, and Johnathan R.W. Temple (2005) Growth econometrics. In P. Aghion and S. Durlauf (eds.), *Handbook of Economic Growth*, vol. 1, pp. 555–677. Amsterdam: Elsevier.

Falk, Martin and Katja Stein (2001) The Impact of Information Technology on High-Skilled Labor in Services. Evidence from Firm Level Data. Mimeo, Yale University.

Fan, Jiwen (1992) Design-adaptive nonparametric regression. *Journal of the American Statistical Association* 87, 998–1004.

Fan, Jiwen and Wenyang Zhang (1999) Statistical estimation in varying coefficient models. *Annals of Statistics* 27, 1491–1518.

Fan, Yianqin and Qi Li (1996) Consistent model specification tests: Omitted variables, parametric and semiparametric functional forms. *Econometrica* 64, 865–890.

Fan, Yianqin, Qi Li, and Stengos Thanasis (1995) Root-N-consistent semiparametric regression with conditional heteroskedastic disturbances. *Journal of Quantitative Economics* 11, 229–240.

Feldstein, M. (2003) Why Is Productivity Growing Faster? NBER working paper 9530.

Galor, Oded (2005) The transition from stagnation to growth: Unified growth theory. In S. Durlauf and P. Aghion (eds.), *Handbook of Economic Growth*, pp. 171–293. Amsterdam: Elsevier.

Galor, Oded and Omer Moav (2000) Ability-biased technological transition, wage inequality and economic growth. *Quarterly Journal of Economics* 115(2), 469–497.

Galor, Oded and Daniel Tsiddon (1997) Technological progress, mobility and economic growth, *American Economic Review* 87(3), 363–382.

Galor, Oded and Joseph Zeira (1993) Income distribution and macroeconomics. *Review of Economic Studies* 60(1), 35–52.

Gordon, Robert J. (2004) Why Was Europe Left at the Station When America's Productivity Locomotive Departed? NBER working paper 10661.

Hoon, Y-S. (2003) Does information technology contributed to economic growth in developing countries? A cross country analysis. *Applied Economics Letters* 10(11), 679–682.

Jorgenson, Dale W. and Khuongs Vu (2005) Information technology and the world economy. *Scandinavian Journal of Economics* 107(4), 631–650.

Kalaitzidakis, Pantelis, Theofanis Mamuneas, Andreas Savvides, and Stengos Thanasis (2001) Measures of human capital and nonlinearities in economic growth. *Journal of Economic Growth* 6, 229–254.

Ketteni, Elena (2009) Information technology and economic performance in U.S. industries. *Canadian Journal of Economics* 42(3), 844–865.

Ketteni, Elena, Theofanis Mamuneas, and Stengos Thanasis (2007) Nonlinearities in economic growth: A semiparametric approach applied to information technology data. *Journal of Macroeconomics* 29, 555–568.

Kourtellos, Andros (2003) Modelling parameter heterogeneity in cross-country regression models. Department of Economics mimeo, University of Cyprus.

Li, Q., C.J. Huang, D. Li, and T. Fu (2001) Semiparametric smooth coefficient models. *Journal of Business and Economic Statistics* 20(3), 412–422.

Mamuneas, Theofanis, Andreas Savvides, and Stengos Thanasis (2006) Economic development and the return to human capital: A smooth coefficient semiparametric approach. *Journal of Applied Econometrics* 21, 111–132.

Masanjah, W.H. and Chris Papageorgiou (2004) The Solow model with CES technology: Nonlinearities and parameter heterogeneity. *Journal of Applied Econometrics* 19, 171–201.

Matteucci, N., Mary O'Mahony, Catherine Robinson, and T. Zwick (2005) Productivity, workplace performance and ICT: Industry and firm-level evidence for Europe and the US. *Scottish Journal of Political Economy* 52(3), 359–386.

Oliner, Stephen D. and Daniel E. Sichel (2003) Information technology and productivity: Where are we now and where are we going? *Journal of Policy Modelling* 25, 477–503.

Pilat, Dirk and Paul Schreyer (2004) The OECD productivity database: An overview. *International Productivity Monitor* 8, 59–65.

Robinson, Peter M. (1988) Root-N-consistent semiparametric regression. *Econometrica* 56, 931–954.

Siegel, Donald (1997) The impact of computers on manufacturing productivity growth: A multiple indicators-multiple causes approach. *Review of Economics and Statistics* 79(1), 68–78.

Stiroh, Kevin J. (1998) Computers, productivity and input substitution. *Economic Inquiry* 36(2), 175–191.

Stiroh, Kevin J. (2002) Information technology and the US productivity revival: What do the industry data say? *American Economic Review* 92(5), 1559–1576.

Timmer, Marcel, Mary O'Mahony, and Bart van Ark (2007) EU KLEMS growth and productivity accounts: An overview. *International Productivity Monitor* 14, 71–85.

van Ark, Bart, Robert Inklaar, and Robert H. McGuckin (2003) The contribution of ICT-producing and ICT-using industries to productivity growth: A comparison of Canada, Europe and the United States. *International Productivity Monitor* 6, 56–63.

Vikram, Nehru and Dhareshwar Ashok (1993) A new database on physical capital stock: Sources, methodology and results. *Rivista de Analisis Economico* 8(1), 37–59.

Vikram, Nehru, Eric Swanson, and Dubey Ashutosh (1995) A new database on human capital stock in developing and industrial countries: Sources, methodology and results. *Journal of Development Economics* 46, 379–401.

APPENDIX

A.1. SPECIFICATION TEST

We use a variant of Fan and Li (1996) to test the null hypothesis for the smooth-coefficient regression, where

$$H_0 : y_i = \alpha(z_i) + x_i'\beta(z_i) + u_i \tag{11}$$

and the alternative is

$$H_1 : y_i = g(x_i, z_i) + u_i \neq \alpha(z_i) + x_i'\beta(z_i) + u_i.$$

Fan and Li (1996) argue that if $u_i = y_i - \alpha(z_i) - x_i'\beta(z_i)$, then $E(u_i/x_i, z_i)$ equals zero if and only if the null hypothesis is true. Let $W_i = (x_i, z_i)$, where x_i and z_i are of dimension q and p, respectively. It is also true that $E[u_i E(u_i/W_i)] = E\{[E(u_i/W_i)]^2\} \geq 0$ and the equality holds iff H_0 holds. An extension of the Fan and Li (1996) methodology results in a test statistic for the null based on an estimator of $n^{-1}\sum_i[u_i f_{zi}]E[u_i f_{zi}/W_i]f(W_i)$, where $f_{zi} = f_z(z_i)$, $f_z(.)$ is the probability density function of z_i, and $f(.)$ is the pdf of W_i.

The test is based on the smooth-coefficient regression residual $\widehat{u}_i = y_i - \widehat{\alpha}(z_i) + x_i'\widehat{\beta}(z_i)$ used to estimate $u_i f_{zi}$ by $\widehat{u}_i \widehat{f}_{zi}$, where $\widehat{f}_{zi}$ is the corresponding kernel estimator of f_{zi} given by $\widehat{f}_{zi} = [1/(n-1)h^p]\sum_{j\neq i} K_{ij}^z$, where $K_{ij}^z = K^z[(z_i - z_j)/h]$, with $K^z(.)$ being a product kernel and h a smoothing parameter. The term $E[\widehat{u}_i \widehat{f}_{zi}/W_i]f(W_i)$ is estimated by $[(n-1)\lambda^{p+q}]^{-1}\sum_{j\neq i}[\widehat{u}_i \widehat{f}_{zi}]K_{ij}$, where $K_{ij} = K(W_i - W_j/\lambda) = K[(x_i - x_j)/\lambda, (z_i - z_j)/\lambda]$, K is a product kernel, and λ is a smoothing parameter. The test statistic then becomes

$$I_n = \frac{1}{n(n-1)\lambda^{p+q}}\sum_i \sum_{j\neq i}[\widehat{u}_i \widehat{f}_{zi}][\widehat{u}_i \widehat{f}_{zj}]K_{ij}. \tag{12}$$

Define $T = n\lambda^{(p+q)/2} I_n/\sqrt{2}\widehat{\sigma}$, where $\widehat{\sigma}^2 = [1/n(n-1)\lambda^{p+q}]\sum_i\sum_{j\neq i}[\widehat{u}_i \widehat{f}_{zi}]^2[\widehat{u}_i \widehat{f}_{zj}]^2 K_{ij}^2$. Using arguments similar to Fan and Li (1996), $T_a^{\sim}N(0,1)$ under the null hypothesis. This forms the basis for the following one-sided asymptotic test for H_0: reject the null at significance level α_0 if $T \succ Z_{a_0}$ where Z_{a_0} is the upper a_0-percentile of the standard normal distribution. A similar test, using a variant based on Fan et al. (1995), can be used to test a general linear partial model, as in Robinson (1988), against a fully nonparametric model. We use a bootstrap version of the above test using the residuals under the null model.

A.2. HAUSMAN TEST

Let y_i denote the dependent variable: x_i denotes a $p \times 1$ vector of variables of interest, possibly endogenous, and z_i denotes a $q \times 1$ vector of exogenous variables that enters the smooth coefficient function $\beta(z_i)$. We also define w_i to denote an $l \times 1$ vector of instrumental variables, where $l \geq p$. The model under the null hypothesis that the x_i' are exogenous can be written as

$$y_i = X_i^T\delta(z_i) + \varepsilon_i, \quad E(X_i^T\varepsilon_i) = 0,$$

but under the alternative that the x_i' are endogenous we have that

$$y_i = X_i^T \delta(z_i) + \varepsilon_i, \quad E(W_i^T \varepsilon_i) = 0,$$

where $\delta(z_i) = (\alpha(z_i), \beta(z_i)^T)^T$ is a smooth but unknown function of z. One can estimate $\delta(z)$ using a local least-squares approach under the null hypothesis, where

$$\widehat{\delta}(z) = \left[(nh^q)^{-1} \sum_{j=1}^{n} X_j X_j^T K\left(\frac{z_j - z}{h}\right) \right]^{-1} \left[(nh^q)^{-1} \sum_{j=1}^{n} X_j y_j K\left(\frac{z_j - z}{h}\right) \right],$$

and under the alternative, following Cai et al. (2006), we use a local IV approach, where

$$\widehat{\delta}_{IV}(z) = \left[(nh^q)^{-1} \sum_{j=1}^{n} W_j X_j^T K\left(\frac{z_j - z}{h}\right) \right]^{-1} \left[(nh^q)^{-1} \sum_{j=1}^{n} W_j y_j K\left(\frac{z_j - z}{h}\right) \right].$$

To test the null hypothesis using a Hausman-type test we bootstrap the contrast of estimators $(\widehat{\delta}_{IV}(z) - \widehat{\delta}(z))$, using the residuals under the null model.