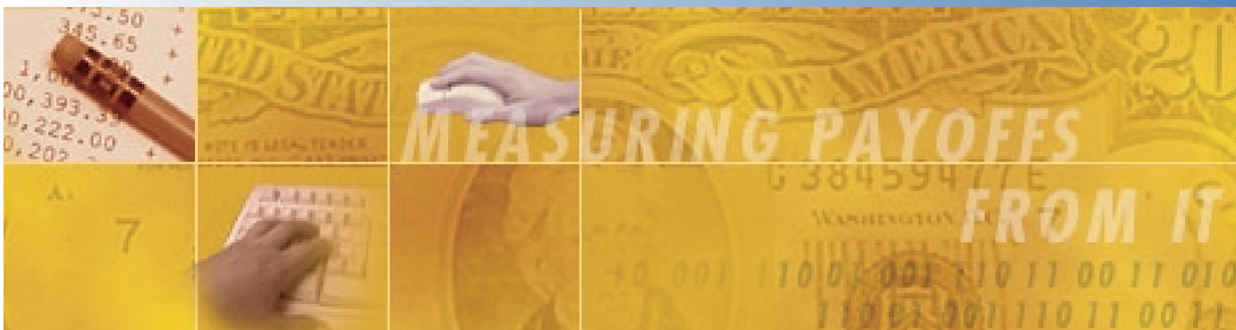
Measuring Payoffs from Information-Technology Investments: New Evidence from Sector-Level Data on Developed and Developing Countries

Authors
Plice, Robert K.
Kraemer, Kenneth L.

Publication Date
2001-07-01



CENTER FOR RESEARCH ON INFORMATION TECHNOLOGY AND ORGANIZATIONS

University of California, Irvine
3200 Berkeley Place
Irvine, CA, 92697-4650
and
Graduate School of Management
UCI

Measuring Payoffs from Information-Technology Investments: New Evidence from Sector-Level Data on Developed and Developing Countries [1]

AUTHORS:
Robert K. Plice
Center for Research on Information Technology and Organizations (CRITO)
Graduate School of Management, University of California, Irvine, Irvine, CA 92697

Kenneth L. Kraemer
Center for Research on Information Technology and Organizations (CRITO)
Graduate School of Management, University of California, Irvine, Irvine, CA 92697

Working paper—please do not cite or distribute without permission of the authors. Revised July 2001

[1] Acknowledgement: This research was supported by grants from the CISE/IIS/CSS Division of the U.S. National Science Foundation and the NSF Industry/University Cooperative Research Center (CISE/EEC) to the Center for Research in Information Technology and Organizations (CRITO) at the University of California, Irvine. Industry sponsors include: ATL Products/Quantum, the Boeing Company, Canon Information Systems, IBM, Nortel Networks, Conexant, Microsoft, Seagate Technology, Sun Microsystems, Whirlpool Corporation. Software support for this research was provided by Quantitative Micro Software

Abstract:

The payoffs from investments in information technology are investigated at the international level by analyzing a database containing six years of output, employment and investment data for six industry sectors in 36 countries. The Solow endogenous-growth model is employed to derive parameters of a Cobb-Douglas production function relating aggregate GDP to levels of three inputs: IT capital, non-IT capital and labor. For the full set of countries we find the coefficients on IT capital in the linear regression model to be significant and positive, indicating productivity payoffs from IT investment during the period. Using the database to estimate actual factor shares, we find that there was a substantial underinvestment in IT compared to the levels predicted by applying neoclassical assumptions. Furthermore, estimates of the marginal products of IT and non-IT capital indicate that IT investments were five to eight times more productive at the margin than non-IT investments. We found that the same overall pattern holds for the subset of the database consisting only of developed countries, but no evidence of similar relationships were found among in the developing-country subset. These results confirm the main findings of earlier country-level investigations into the so-called productivity paradox, while diverging from earlier papers in terms of the relative elasticities of IT and non-IT capital. By applying the Solow model to sectors as the unit of analysis, we have avoided the need to estimate capital-stock variables from capital-flow variables and to account for investments in human capital. We speculate that this methodology contribution may account for the differences between our elasticity estimates and those of earlier studies.

1. Introduction

An important and continuing issue in information-technology research concerns the question of linkage between investments in IT capital and the productivity performance of economies at large. Considering the vast amount of spending on IT in the United States and worldwide during the decades leading up to the 1990s, it was suggested by early observers of the so-called productivity paradox that there was little to point to in terms of specific productivity benefits (e.g., Roach, 1988). As economists and IT researchers pursued this puzzle during subsequent years several explanations emerged, including the David (1990) hypothesis that there may be a substantial lag between investment and payoff as firms and industries restructure to capture the benefits of technology; the Griliches (1994) hypothesis that measurement problems (especially in the services sectors) may be to blame; and the observation (Oliner and Sichel, 1994, 2000) that even though the rate of investment in IT capital had been increasing, it comprised only a small percentage of total capital until recently. Research at the firm level (Loveman, 1994, Lichtenberg, 1993, Barua et al., 1995, Brynjolfsson and Hitt, 1996, Lehr and Lichtenberg, 1999, Gurbaxani et al., 1998) and at the sector level within the United States (Morrison and Berndt, 1991, Oliner and Sichel, 1994) continued through the 1990s, even as the end of the decade saw an upturn in U.S. labor productivity. As a result, the predominant, though not universal, view is that IT investments have played a significant role in raising trend productivity in the United States (Jorgenson et al., 2000, Oliner and Sichel, 2000, Council of Economic Advisors, 2001).

At the international level, however, the issue has remained more obscure. Dewan and Kraemer (2000) used series from the Penn World Tables, combined with IDC data on IT shipments, to estimate a production function for a sample of developed and developing countries, and obtained elasticity estimates for IT capital that were positive and significant for developed countries, but not for developing countries nor for the combined sample. Pohjola (2001) used a sample of 39 countries and estimated production-function parameters following an approach detailed by Mankiw, Romer and Weil (1992), and found that IT capital was significant for the OECD subset but not for the entire panel.

Schreyer (2000) used a growth-accounting framework to assess the contribution of information and communications technology (ICT) to economic growth in the G7 countries, and found that ICT capital is an important contributor, especially in the United States. Together, these papers have begun to fill in the pieces relating to the international dimensions of the IT-returns puzzle, suggesting that investments in IT have had a positive payoff when undertaken in developed countries, but perhaps not in the developing world.

Yet, there are unresolved issues associated with these results. First, the Dewan and Kraemer and Pohjola studies obtained quite different estimates of the output elasticity of IT capital: Pohjola found a much greater effect on output within developed countries than did Dewan and Kraemer. Furthermore, the Dewan and Kraemer research depends on an extrapolation to impute estimates of the stock levels of IT and non-IT capital from the available series on investment flows, giving rise to a possible source of misspecification. The earlier studies also each had limitations regarding their treatment of human capital (see Section 6 below).

This paper reports on research that uses a data source that has not been analyzed previously. It also overcomes the limitations of the earlier papers by extending the methodology used by Mankiw, et al. and Pohjola in such a way that estimates of stock IT, non-IT and human capital levels are not required. The resulting findings are complementary to earlier research and exploit the unique structure of the database.

The following research questions are addressed, relative to the years 1991-1996:

1. To what extent did investments in IT capital enhance productivity at the international level?
2. Was there overinvestment or underinvestment in IT capital during the subject years?
3. What were the relative returns on investment in IT and non-IT capital?
4. Did the payoffs to IT-capital investment differ between developed and developing countries?

We have found that investments in IT capital at the international level have productivity payoffs and that there was a substantial underinvestment in IT during the period 1991-1996, at least among developed countries. Furthermore, we have found the payoffs to IT capital to be substantially greater, at the margin, than for non-IT capital. These findings help to resolve the discrepancies between the earlier studies at the international level, and lend support to the thesis that the productivity paradox, if it ever existed, had largely disappeared by the middle part of the 1990s.

The plan of this paper is as follows. In Section 2, we describe the data and the analytical division between developed and developing countries. In Section 3 we develop the analytical model and point out the similarities to and departures from earlier research. In Section 4 we explore the econometrics involved in fitting the data to the model. In Section 5, we derive estimation results and interpret the findings in terms of the initial research questions. Finally, in Section 6, we conclude by comparing the results to those of previous studies.

2. Data

Sources of data

Data for this research was obtained from two independent sources. Series on output, employment and capital investment for 36 countries were obtained from the United Nations (1999), which broke the data down by industry sector. The list of countries is shown in Table 1, which also indicates the division of countries between the developed and the developing world. The specific data series used included sector GDP, gross fixed capital investment (GFCF), employment hours, and exchange rates. All data was expressed in 1990 dollars, using the official exchange rates for conversion purposes.

Insert Table 1 about here

The UN data was augmented by series obtained from IBM[2], giving total IT investment in 1990 dollars. The industry data was also broken down by sector, but the sector definitions differed somewhat from those used by the UN. Table 2 gives the definitions used by the two data sources, and shows the matching that was performed in producing the composite database. Although we attempted to match the sector definitions as closely as possible, it is recognized that remaining discrepancies will be a possible source of model misspecification. However, the success in fitting the data to the analytical model, as described subsequently, suggests that the misspecification effects are not severe.

Insert Table 2 about here

The assignment of countries to the developed and developing categories, as shown in Table 1, conforms to that of Dewan and Kraemer (2000), who showed that there is a clear clustering of the two groups when productivity is plotted against IT investment. We present a similar plot in Figure 1, where GDP per employee (relative to the United States) is graphed on the horizontal axis versus the level of IT investment as a percent of GDP on the vertical axis, and the points for developed and developing countries are distinguished. The resultant clustering is taken as justification for treating the developed and developing subsamples as having distinct characteristics in terms of their application of information technology to production processes.

Insert Figure 1 about here

3. Analytical model

The Dewan and Kraemer paper follows the approach taken by much of the empirical research into IT returns, in that it uses a production-function framework to parameterize the relationships between investment and productivity. In its textbook formulation (see, e.g., Mas-Colell et al., 1995 p. 129), a production function gives the maximum amount of output that can be produced from a given combination of inputs as a function $Y(\mathbf{z})$, where $\mathbf{z} = (z_1, \ldots, z_n)$ is a vector giving amounts of the n inputs to the production process. We will seek to estimate the parameters of an aggregate production function that gives the level of total output (or GDP) as a function of the three inputs IT capital, non-IT capital, and labor:

$$Y = Y(K_1, K_2, AL) \tag{3.1}$$

where K_1 is the level of non-IT capital stock and K_2 is the level of IT-capital stock. We follow Mankiw, Romer and Weil (1992) in using the term AL to represent units of

[2] IBM Corporation, information provided to authors.

effective labor, where L is the actual labor input and A is the level of technology available in the aggregated industries.

Although the database contains series for GDP and labor, which can be applied directly in estimating the parameters of (3.1), we have no series that show stock levels of the two kinds of capital; rather, we have data only on capital *investment* for the years in question. Before estimating the production function, then, we require a method for converting capital flows to capital stock. One approach is to extrapolate investment flows back to some base year (possibly using a model of technology diffusion), and then aggregate forward, using assumed rates of depreciation, to derive stock levels during the subject years (this is similar to the method used by Dewan and Kraemer to derive stock levels of IT capital). Although such techniques are well grounded in both theory and accepted econometric practice, we have two motivations for seeking an alternative. First, the data series we use are not complete for all countries and sectors with regard to non-IT capital, so we wish to avoid extrapolating on the basis of a small number of available data points. Second, we feel that a method that requires fewer assumptions in terms of investment and depreciation models, if available, will be preferable from the standpoint of internal validity.

Mankiw, et al. used a database containing capital-investment flows and employment data for a number of developed and developing countries to test the predictions of an exogenous-growth model proposed in a classic paper by Robert Solow (1956). We will follow their basic approach, but we will diverge and extend their theory as needed in order to recognize the peculiar nature of price deflation for IT capital and to utilize the sectoral structure of the database to control for the effective level of technology. We begin by presenting the basic Solow model, and then proceed—in a manner similar to Mankiw, et al.—to derive the form of an estimable linear model.

The Solow growth model eliminates the need to estimate capital stock by positing that an economy will exhibit a stable, equilibrium ratio of capital to labor when the level of investment and the growth rate of employment are taken as exogenous. Since the levels of capital investment and both the levels and growth rates of employment are in the database for each of the countries and sectors, we can use Solow's approach to determine the capital-labor ratio, which then provides an implicit estimate of capital stock. The assumptions of the model are fairly parsimonious and are by no means heroic in the context of previous IT-productivity research. Specifically, we assume that:

1. all labor and capital are employed (tautological in this context, as the database contains only those levels of labor and capital that were actually measured in production);
2. the production technology is one of constant returns to scale; and
3. the production technology exhibits diminishing marginal products in capital.

Solow looked for a relationship to describe the path that real capital accumulation must follow if all labor and capital are to be employed. Before applying the Solow model to the data, however, we must consider the characteristics of IT capital that may require us to modify the analysis.

When considering traditional types of capital, one can generally ignore the possibility that monetary investment flows represent nominal, rather than real, increases in capital stock, because the rates of price and quality change in buildings, traditional machinery and equipment are relatively limited and usually well behaved. For computer capital, however, the rate of nominal investment must be adjusted both for rapid quality change and for the fact that a portion of new investment goes to replace older technology that is still fully functional. For example, a firm may install a new ERP system to replace an older system that did only general-ledger accounting; in this case a portion of the ERP investment is not new productive capital but merely replicates the existing accounting capability. We therefore define the term

$$\lambda_i = \left(\frac{1-\tau_i}{1-\mu_i} \right) \tag{3.2}$$

as the conversion factor for translating nominal spending to real spending for capital type i, where τ_i is the proportion of investment that replaces existing, undepreciated capital stock, and μ_i is the rate of price deflation (typically large for computer capital). We have no reason to assume that the λ terms will vary for different countries in the database, nor are we aware of research that would allow the specification of different values of λ for different sectors. Our approach is to make the estimation model conditional on fixed values of λ for the two types of capital, and then to explore the implications of different assumptions about the λ terms. Thus, if v_i is the share of output spent on capital type i, then $v_i Y$ is the amount of nominal investment and $s_i Y$ the amount of real investment, where

$$s_i = \lambda_i v_i \tag{3.3}$$

Using this terminology, the basics of the Solow model can be utilized in the present context. The rate at which the real stock of capital type i increases is

$$\dot{K}_i = s_i Y\left(K_1, K_2, AL\right) - \delta K_i \tag{3.4}$$

where the notation $\dot{K}$ stands for $\frac{dK}{dt}$ and δ is the rate of depreciation that applies to all capital.

Letting r_i stand for the ratio of the stock quantity of capital type i to units of effective labor, we have $K_i = r_i AL$, and if g and n represent the growth rates of technology and labor, respectively, then at time t

$$K_i = r_i A(0) L(0) e^{(g+n)t} \tag{3.5}$$

where $A(0)$ and $L(0)$ are levels of technology and labor at time $t = 0$. Differentiating (3.5) with respect to time, we find

$$\dot{K}_i = \left(\dot{r}_i + (n+g) r_i\right) AL \tag{3.6}$$

Combining (3.4) and (3.5), factoring AL out of the production function by the assumption of constant returns to scale, and rearranging we obtain

$$\dot{r}_i = s_i Y\left(r_i, r_j, 1\right) - r_i\left(n + g + \delta\right) \tag{3.7}$$

which is a differential equation describing the rate of change in the capital-labor ratio for capital type i as a function of investment, effective-labor growth, and the capital-labor ratio itself, conditional on the capital-labor ratio for capital type j.

Solow pointed out that, under the assumption that the production function exhibits diminishing marginal products, the path of capital accumulation described by (3.7) will result in a stable equilibrium ratio r_i. To see this, refer to Figure 2, which shows the two terms from the right-hand side of (3.7) plotted simultaneously, assuming a fixed value of r_j. Because of the assumption of diminishing marginal products, there is a single non-degenerate point of intersection of the two curves at the value r_i^*, which represents the stable equilibrium. If the value of r_i were to be moved by some exogenous shock to a point below r_i^*, say to r_i', then by (3.7) we see that $\dot{r}_i > 0$ and that r_i will increase over time. Similarly, if a shock were to move the ratio to the point r_i'', then $\dot{r} < 0$ so the ratio will again trend back to the equilibrium value.

<u>Insert Figure 2 about here</u>

Before we can use this equilibrium concept to develop an estimable linear equation, we require an explicit form for the production function. Following earlier research in which the use of the Cobb-Douglas production function is pervasive, and relying on the results of Dewan and Min (1997)—who found, using the CES-translog form, that substitution elasticities were close to unity—we adopt the Cobb-Douglas model and note that its restricted form satisfies the earlier assumptions of constant returns to scale and diminishing marginal products. Our production function can then be written as

$$Y\left(K_1, K_2, AL\right) = K_1^{\beta_1} K_2^{\beta_2} \left(AL\right)^{1-\beta_1-\beta_2} \tag{3.8}$$

and AL can be factored out (by constant returns to scale) to derive

$$Y\left(r_1, r_2, 1\right) = \frac{K_1^{\beta_1}}{\left(AL\right)^{\beta_1}} \frac{K_2^{\beta_2}}{\left(AL\right)^{\beta_2}} = r_1^{\beta_1} r_2^{\beta_2} \tag{3.9}$$

This can be substituted into (3.7) to get

$$\dot{r}_i = s_i r_i^{\beta_i} r_j^{\beta_j} - (n + g + \delta) r_i \tag{3.10}$$

Since the Solow equilibrium is stable, our expectation is that $\dot{r} = 0$, so we have

$$s_i r_i^{\beta_i} r_j^{\beta_j} = (n + g + \delta) r_i \tag{3.11}$$

and, therefore,

$$\frac{s_i}{s_j} = \frac{r_i}{r_j} \tag{3.12}$$

By substituting (3.12) into (3.11), after some manipulation and expansion of r_i, we can obtain an expression for the equilibrium capital-labor ratio in terms of investment shares and growth rates:

$$K_i = AL\left(\frac{s_i^{1-\beta_j} s_j^{\beta_j}}{n + g + \delta}\right)^{\frac{1}{1-\beta_i-\beta_j}} \tag{3.13}$$

which gives the stock level of capital in terms of the flow variables that are available in the database. The expressions from (3.13) for the two kinds of capital can now be substituted into the production function of (3.8) to obtain

$$\frac{Y}{L} = A(0)e^{gt}(n + g + \delta)^{\frac{-(\beta_1+\beta_2)}{1-\beta_1-\beta_2}} s_1^{\frac{\beta_1}{1-\beta_1-\beta_2}} s_2^{\frac{\beta_2}{1-\beta_1-\beta_2}} \tag{3.14}$$

This expression will hold for any time t, so we choose to set $t = 0$ and take logarithms, resulting in the linear model

$$\begin{aligned} &\ln\left(\frac{Y}{L}\right) = \\ &\ln A + \left(\frac{\beta_1}{1-\beta_1-\beta_2}\right)\ln s_1 + \left(\frac{\beta_2}{1-\beta_1-\beta_2}\right)\ln s_2 - \left(\frac{\beta_1+\beta_2}{1-\beta_1-\beta_2}\right)\ln(n + g + \delta) \end{aligned} \tag{3.15}$$

which, provided that we can make reasonable assumptions about the rate of depreciation δ and the rate of growth in technology g, is close to being an estimable equation; it remains to model the level of technology A in terms of available data series.

To accomplish this, we depart again from the model described by Mankiw, et al. in order to take advantage of the unique structure of the database. Because the data series are organized by sector, we can exploit the tendency for production technologies within a sector to be comparable across countries, while retaining the ability to distinguish between technologies used in developed and developing countries. Because we have a complete panel for the United States, we make the identifying assumption that the level of technology in each sector is proportional to U.S. labor productivity in that sector, allowing for a different constant of proportionality between developing and developed countries. That is, we assume

$$A_{md} = \alpha_d \frac{\tilde{Y}_m}{\tilde{L}_m} \tag{3.16}$$

where m indexes the sector, d is a dummy variable distinguishing developed and developing countries, and $\tilde{Y}_m$ and $\tilde{L}_m$ are GDP and units of labor for sector m in the United States. In logarithms, we now take

$$\ln A_{md} = \ln \alpha_d + \ln\left(\frac{\tilde{Y}_m}{\tilde{L}_m}\right) + \varepsilon_{md} \tag{3.17}$$

where ε_{md} is a Solow-style innovation, or shock, specific to a sector within a level of economic development. The linear model can then be written as

$$\begin{aligned}
&\ln\left(\frac{Y/L}{\tilde{Y}/\tilde{L}}\right)_{md} = \\
&\ln \alpha_d + \left(\frac{\beta_1}{1-\beta_1-\beta_2}\right)\ln s_{1_{md}} + \left(\frac{\beta_2}{1-\beta_1-\beta_2}\right)\ln s_{2_{md}} + \left(\frac{-\beta_1-\beta_2}{1-\beta_1-\beta_2}\right)\ln\left(n_{md}+g+\delta\right) + \varepsilon_{md}
\end{aligned} \tag{3.18}$$

The only remaining issue is that the database contains nominal investment flows, not the real levels required to estimate (3.18). A correction for this would be to substitute (3.3) into (3.18) getting

$$\ln\left(\frac{Y/L}{\tilde{Y}/\tilde{L}}\right)_{md} = \left(\frac{\beta_1}{1-\beta_1-\beta_2}\right)\ln\lambda_1 + \left(\frac{\beta_2}{1-\beta_1-\beta_2}\right)\ln\lambda_2 + \ln\alpha_d + \left(\frac{\beta_1}{1-\beta_1-\beta_2}\right)\ln v_{1_{md}} + \left(\frac{\beta_2}{1-\beta_1-\beta_2}\right)\ln v_{2_{md}} + \left(\frac{-\beta_1-\beta_2}{1-\beta_1-\beta_2}\right)\ln\left(n_{md}+g+\delta\right)+\varepsilon_{md} \tag{3.19}$$

Because our main objective is to identify the production-function parameters β_1 and β_2, it is sufficient to estimate the coefficients on the terms $\ln v_1$ and $\ln v_2$ in this model; we will then have two equations in two unknowns, permitting us to solve for the β terms. Regardless of what values the λ terms take on, they will not affect the estimation of the coefficients of interest (they will simply change the coefficient on the constant term in the regression model), so we simplify (3.19) by taking

$$\ln\left(\frac{Y/L}{\tilde{Y}/\tilde{L}}\right)_{md} = c_d + \left(\frac{\beta_1}{1-\beta_1-\beta_2}\right)\ln v_{1_{md}} + \left(\frac{\beta_2}{1-\beta_1-\beta_2}\right)\ln v_{2_{md}} + \left(\frac{-\beta_1-\beta_2}{1-\beta_1-\beta_2}\right)\ln\left(n_{md}+g+\delta\right)+\varepsilon_{md} \tag{3.20}$$

to be the estimable, linear model, where the c_d term represents a composite effect stemming from the α and λ terms in the earlier expression. If we estimate (3.20) in the form given, we will be using up an extra degree of freedom, because the sum of the first two coefficients is theoretically restricted to be equal in magnitude and opposite in sign to the third. However, by first estimating the model with the extra term included we will follow Mankiw, et al. and Pohjola in using the result as a test of how well the Solow-equilibrium model does in predicting relationships in the database. If we see that the coefficients do indeed conform to the predicted restriction, we will have increased confidence that the model appropriately parameterizes the data.

4. Econometric issues

To perform the linear regressions specified by (3.20), we must first construct the dependent and independent variables by appropriately combining available series from the database. For the dependent variables v_1 and v_2 we average—for each of the six sectors, and separately for the developed and developing subsamples—the levels of capital spending over all years and all countries:

$$v_{md} = \frac{\sum_{c=1}^{C_d} \frac{\sum_{t=1}^{T_{mc}} \frac{k_{mc}(t)}{Y_{mc}(t)}}{T_{mc}}}{C_d} \tag{4.1}$$

Here an adjustment is made for missing values by modifying the divisors T_{mc} and C_d, which stand for the number of time periods and countries, respectively, that go into the average. For the independent variable we take the similar calculation

$$\left(\frac{Y}{L}\right)_{md} = \frac{\sum_{c=1}^{C_d} \frac{\sum_{t=1}^{T_{mc}} \frac{Y_{mc}(t)}{L_{mc}(t)}}{T_{mc}}}{C_d} \tag{4.2}$$

over the years and countries, and we divide by the United States productivity level in that sector, computed as

$$\left(\frac{\tilde{Y}}{\tilde{L}}\right)_{m} = \frac{\sum_{t=1}^{6} \frac{\tilde{Y}_m(t)}{\tilde{L}_m(t)}}{6} \tag{4.3}$$

(there are no missing values in the database for the United States). Note that the averages are unweighted; that is, small countries count the same as large countries in determining the variables' values, because the perspective is that each sector within a country is an instance of an economy in Solow equilibrium. By observing as many equilibrium ratios as possible and averaging them together, we limit our vulnerability to the noisiness inherent to national income and product account measurements and to the effects of country-specific exogenous shocks that may temporarily move an economy away from the theoretical equilibrium relationship.

The growth rate of employment within each country and sector is obtained by using ordinary least squares (OLS) to estimate the regression model

$$\ln L(t) = a + \hat{n}t + e \tag{4.4}$$

where L is the employment level, and taking the time-trend coefficient as the measured employment growth rate. These are then averaged for each sector, separately for developed and developing countries, using

$$\left(n+g+\delta\right)_d = \frac{\sum_{c=1}^{C_d} \hat{n}}{C_d} + .06 \tag{4.5}$$

Here we have followed Mankiw, et al. in using a constant term to approximate the combined rates of depreciation and technology growth, based on citations of earlier research that suggest a value for δ of about .03 or .04 and a value for g of about .02. After presenting the baseline estimation results below, we explore the effect of changes in the assumption that $g+\delta = .06$.

Having constructed the necessary variables, we are in a position to proceed with the estimation of the coefficients of the linear model given by (3.20). For an initial estimate, we employ OLS and we obtain the results shown in Table 3. The coefficients have the expected signs, and the adjusted L value is satisfactory in that almost 90% of the variance in the dependent variable is explained. However, the *t* statistics on the coefficients are low and we are unable to reject the null hypothesis of any of them being individually equal to zero. A high level of explained variance coinciding with low significance levels on the individual coefficients is often an indication that one or more assumptions of the regression model are violated. In addition, it does not appear that the model's theoretical restriction that the magnitude of the sum of the first two coefficients is equal to the third holds (although we cannot reject the null hypothesis that the restriction is true at a probability level for a type-I error lower than 48%).

Insert Table 3 about here

A review of the assumptions that underlie OLS can illuminate these issues (see Greene, 1997 Section 6.3). Key among the requirements of OLS is that the residuals have zero mean and uniform variance, and that they are uncorrelated. In terms of the model and database, this can be expressed as

$$E\left(\varepsilon\right) = 0 \tag{4.6}$$

and

$$E\left(\varepsilon\varepsilon'\right)=\sigma^2\boldsymbol{I}_{12}=\begin{pmatrix}\sigma^2 & 0\\ 0 & \sigma^2\end{pmatrix}\otimes\boldsymbol{I}_6 \tag{4.7}$$

Recall, however, that we have an explicit interpretation of the residual vector $\boldsymbol{\varepsilon}$: it consists of technology innovations. We should not, therefore, expect the assumption of uncorrelated residuals to be satisfied. In particular:

1. the impact of an innovation on productivity can be expected to vary between developing and developed countries, leading to *heteroscedasticity*; and
2. although the impact of innovations may vary by sector, there will be positive covariance between the residuals representing the same sector in developed and developing countries, leading to *autocorrelation*.

Given these violations of its assumptions, the OLS estimator shown in Table 3 is inefficient, and the standard errors are wrong (Greene, p. 498). Instead of assuming the structure shown in (4.7), we should use

$$E\left(\boldsymbol{\varepsilon\varepsilon}'\right)=\begin{pmatrix}\sigma^2_{\substack{\text{developed}\\ \text{developed}}} & \sigma^2_{\substack{\text{developed}\\ \text{developing}}}\\ \sigma^2_{\substack{\text{developed}\\ \text{developing}}} & \sigma^2_{\substack{\text{developing}\\ \text{developing}}}\end{pmatrix}\otimes\boldsymbol{I}_6 \tag{4.8}$$

and apply the method of generalized least squares (GLS), which will produce an unbiased and efficient estimator, sometimes referred to as the Parks (1967) estimator. To do this, however, we would have to know the values for each of the σ^2 terms of (4.8). In the absence of such knowledge, the best we can do is find consistent estimators for each covariance term, and use the method of feasible GLS (FGLS, Greene Section 11.4). To obtain such a consistent estimator, we start with the residual vector from the OLS regression of Table 3 and calculate

$$\hat{\sigma}^2_{d_1 d_2}=\frac{\sum_{m=1}^{6}\varepsilon_{d_1 m}\varepsilon_{d_2 m}}{6} \tag{4.9}$$

We use these covariance estimators to run the GLS procedure, and again use the residual vector to calculate (4.9). This calculation is iterated, comparing the coefficient estimates at each stage to those of the previous cycle, until it is determined that the estimator has converged. We thus obtain the FGLS estimator—iterated to convergence—of the model of (3.20), and the results are given in Table 4. As with the OLS estimator, the R^2 value of the regression is quite high; however, we now note the remarkable conformity with the model's prediction that the magnitude of the sum of the first two coefficients will equal the third; in fact, the relationship appears to be almost exact. The *F* test on the null hypothesis that this restriction is valid fails to reject even if we set the probability of a type-I error at 97%, which justifies the imposition of the theoretical restriction. Accordingly, we estimate the model again to take advantage of the extra degree of freedom.

Insert Table 4 about here

The results of the restricted regression using FGLS is shown in Table 5. The coefficient estimates have changed only slightly from those in the unrestricted model, but we now have significance on each of the coefficients at a *p* value of 0.01, and continue to show an adjusted R^2 of around 90%.

Insert Table 5 about here

In reviewing these results, it should be noted that the extraordinarily close correspondence between the coefficient estimates and their predicted relationship—which was in turn derived from Solow's prediction of a stable ratio of capital to labor—gives credence to the assertion that the model has successfully parameterized the data. By first estimating the unrestricted model and checking that the theoretical coefficient relationships hold within the database—which was constructed with series from different sources having slightly different sector definitions—we gain confidence both in the strength of the model's descriptive ability and in the integrity of the data. We take the Table 5 result as a baseline estimate for the purpose of evaluating the major research questions.

5. Estimation results and analysis

Research question 1: Productivity returns to IT investment

Turning to the first such research question, the results in Table 5 give support to the following:

> *Proposition 1:* **Investment in IT capital had a positive productivity payoff among the sectors and countries in the database during the years 1991-1996.**

This proposition is justified by the positive and significant coefficient on the share of GDP invested in IT capital, which indicates that relative productivity—the dependent variable—increases with spending on IT.

Research question 2: Level of investment in IT

To investigate the second research question, we must identify the parameters of the Cobb-Douglas production function given by (3.8). Using the coefficient estimates from Table 5, along with the expressions for the coefficients in terms of β_1 and β_2 contained in (3.20), we can solve two equations in two unknowns and obtain the values for the production-function parameters, as shown in the column (2) of Table 6. In the Cobb-Douglas formulation, these are interpretable as the output elasticities of non-IT and IT capital. Under the neoclassical assumption that factors of production are paid their marginal products, we can reinterpret the elasticities as factor shares, because a factor share is simply the marginal product times the amount of the factor available divided by total output; that is:

$$s_i = \frac{\partial Y}{\partial K_i}\frac{K_i}{Y} \tag{5.1}$$

which is exactly the same as the expression for the output elasticity of factor K_i. Under this reinterpretation it makes sense to sum the factor shares for non-IT and IT capital to form an estimate of the total share of GDP paid to capital in the aggregate world economy represented by the database, shown as the total of column (2), Table 6. This result gives us a second opportunity to check the model's success at predicting relationships in the database, because we can use the original raw data series to compute

$$k_i = \sum_{c=1}^{36} \sum_{m=1}^{6} \frac{\sum_{t=1}^{T_{cm}} k_{i_{cm}}}{T_{cm}} \tag{5.2}$$

which is the total spending in the database on capital type i with T_{cm} adjusted for missing values, as usual. Similarly, we can compute worldwide output by using the summation

$$Y = \sum_{c=1}^{36} \sum_{m=1}^{6} \frac{\sum_{t=1}^{T_{cm}} Y_{cm}}{T_{cm}} \tag{5.3}$$

Note that these aggregations—unlike those used in preparing the inputs to the regression model—are weighted averages so that large economies count for proportionately more than small economies in computing the totals. Dividing (5.2) by (5.3) gives us the database-derived factor shares for each type of capital, which—because of the proportional weighting—are not directly derivable from the unweighted averages used to perform the regressions. However, as shown in column (3) of Table 6, the actual total share of GDP paid to capital derived from the database using (5.2) and (5.3) matches almost exactly the predicted share implied by the production-function parameterization. This remarkably good fit is a second source of confidence that the theoretical model is successful at representing the actual relationships in the data.

Insert Table 6 about here

However, although the fit between prediction and measurement is nearly exact with regard to total capital spending, Table 6 shows a significant disparity with regard to the breakdown between non-IT and IT capital. To understand why the model can be good at predicting the overall capital share yet fail to predict the individual shares, recall that the differential equation (3.7) was used—as illustrated in Figure 2—to establish an equilibrium capital-labor ratio for capital type i conditional on the equilibrium ratio for capital type j. There is, therefore, one degree of freedom in the system; the ratios for the two types of capital can vary as long as they sum to the set total factor share for all capital. But, if the economy maximizes output by paying all factors their marginal products (Mas-Colell et al., 1995 p. 137), the factor shares will equal the elasticities by the argument embodied in (5.1); therefore, if we measure different shares from those predicted by the elasticities, the conclusion must be that levels of investment in the two types of capital are not consistent with productivity maximization. We thus have support for the following:

> ***Proposition 2:* There was substantial underinvestment in IT capital among the sectors and countries in the database during the years 1991-1996.**

Referring again to column (3) of Table 6, if the world economy represented by the database had acted to maximize GDP, it would have invested 3.4 times as much in IT capital as it actually did.

Thus far, the analysis has ignored the distinction between nominal and real spending levels; that is, we have not accounted for the λ terms defined in (3.2) (to put it another way, we have assumed that $\lambda_1 = \lambda_2 = 1$). For non-IT capital we have no motivation to revise this, because the database contains constant-dollar values and there is no reason to believe that the rate of price change for ordinary capital is not well represented by the GDP price deflator. IT capital is a different matter, because there is both a significant amount of per-period price deflation (or quality improvement, if looked at from the opposite perspective) and a high level of spending on upgrades to existing IT hardware and software that is still fully functional. We should, therefore, consider the effect that different assumptions for the value of λ_2 will have on the analysis.

We start by establishing a range of possible values for λ_2, recognizing that support for the assertion of an underinvestment in IT capital will diminish as λ_2 increases; thus, we are most concerned with exploring values in the range $\lambda_2 > 1$. It is important to note that even in the presence of a relatively high price deflator μ the baseline assumption of $\lambda = 1$ may still be reasonable. To better appreciate the interaction of the μ parameter with the τ parameter—which captures the amount by which existing IT capacity is upgraded, rather than expanded, by new investment—one can think in terms of the illustration contained in Table 7. In this example, the values of μ and τ are equal, so that a nominal IT investment, even though larger in real terms (i.e., in comparison with the existing capital stock), is only partially additive to the base stock level; thus the real increase in productive IT capacity equals the nominal increase. At another extreme, we could ignore the countervailing effect of the τ parameter entirely and use an estimate of μ derived from the so-called Moore's law: that the effective price of computers is halved every 18 months. Under this assumption we would take $\lambda_2 = 1.5$. The range $1 \le \lambda_2 \le 1.5$, by this argument, contains the reasonable set of possibilities that should be explored.

Insert Table 7 about here

Columns (5) and (6) of Table 6 restate the estimates of the amount of underinvestment in IT capital using the Moore's law assumption. Although this would reduce the estimate of the absolute amount by which the world economy should have increased its spending on IT capital, the conclusion stated in Proposition 2 is still supported.

The other thus-far-unexplored assumption is that the combined rates of technology growth and depreciation are equal to a fixed 6% per year. To assess the sensitivity of the above results to this assumption, all of the previous analysis is repeated in Table 8, conditional on values in the range $.02 \le g + \delta \le .1$. With regard to the coefficient restrictions, there is clearly a minimum of the *F* statistic at a value of $g + \delta$ somewhere close to 0.06. Even if we assume a value substantially removed from 0.06, however, Table 8 shows that the thrust of Proposition 2 would still be supported; that is, there is substantial underinvestment in IT capital throughout the range of possible values for $g + \delta$. It can also be seen that the combined choices of $\lambda_2 = 1$ and $g + \delta = .06$ are better supported by the internal-validity checks (i.e., the regression-coefficient restriction and equality of total factor shares) than are the other combinations considered.

Insert Table 8 about here

Research question 3: Relative returns on investment

Although Propositions 1 and 2 have established that IT spending had positive payoffs in terms of productivity and output, we also seek to quantify the actual return on an investment in IT capital and compare it to the return on investment for non-IT capital.

The marginal products tell us the output payoffs from investing an additional small amount in each type of capital, so we proceed to derive them using the database series. First, (3.7) can be manipulated to obtain

$$\frac{K_i}{Y} = \frac{s_i}{g+n+\delta} \tag{5.4}$$

therefore, given the factor shares extracted from the database as described above and an estimate for the world-wide growth rate of labor, the marginal products can be calculated as

$$\frac{\partial Y}{\partial K_i} = \beta_i \left(\frac{g+n+\delta}{s_i} \right) \tag{5.5}$$

To get the required estimate of n, we use $\hat{n}$ from an OLS estimation of the regression model

$$\ln L_{mc}\left(t\right) = a + \hat{n}t + \varepsilon\left(t\right)_{mc} \tag{5.6}$$

over all countries c and sectors m. The resultant marginal products are shown in Table 9. Depending on the choice of λ_2, a marginal investment in IT capital is estimated to have returned 5 to 8 times as much as an investment in non-IT capital. This lends support to the following:

> ***Proposition 3:*** **Marginal investments in IT capital provided a substantially higher return than non-IT capital investments among the sectors and countries in the database during the years 1991-1996.**

Insert Table 9 about here

Research question 4: Developed vs. developing countries

The final research issue is to determine whether or not the findings extend equally to developing and developed countries. The most straightforward way to investigate this is to repeat the regression estimates separately for the two subsamples, and compare the findings to the overall sample. For this step we can make use of OLS, because the problems of heteroscedasticity and autocorrelation represented by (4.8) will not be present. First, we estimate the model for the developed subsample, and give the results as Table 10. Even with the small number of observations, the adjusted R^2 value shows about 75% of the variance in the dependent variable to be explained.

Insert Table 10 about here

The small number of degrees of freedom has raised the p value at which we can claim significance for the coefficients, but both terms are still significant at the 5% level. To determine whether or not the amount of underinvestment in IT is comparable to the worldwide sample, we again solve for the production-function parameters, interpret them as predicted factor shares, and compare to the actual values contained in the database. The results, shown in Table 11, indicate a similar pattern of underinvestment to that noted earlier for the full sample; however, the underinvestment appears to be more pronounced in the developed countries than in the full world economy.

Insert Table 11 about here

Finally, we estimate the regression model for the developing sample, and give the results in Table 12. Here we see that the model appears to explain very little of the variance in the dependent variable, and the coefficients cannot be distinguished from zero. There are several possible technical explanations for the lack of fit, including:

1. We have fewer countries in the database for the developing subsample than the developed subsample, and the countries we have contain more missing values. This may be due to an overall poorer quality in national accounts data for the developing world.

2. The neoclassical assumptions may not hold in the developing world due to subsidy policies and investment decisions made through central planning rather than by market processes.

Insert Table 12 about here

Regardless of the explanation, the confirmation of the positive payback effects from all types of investment in the developed countries, and the lack of confirmation for the developing countries, lends support to the following:

Proposition 4: **The extent of underinvestment is larger among developed countries than in the full sample, and the data provides no evidence of a payoff to IT in the developing sample.**

6. Discussion

Propositions one through four together indicate that investments in IT capital, at least in the developed world, provided substantial benefits in terms of labor productivity and return on investment in the subject countries during the period of time studied. This conclusion is bolstered by the evident success of the analytical model in parameterizing the available data. We also have observed that the results appear to hold for the developed countries when considered on their own, but are not statistically different from zero for developing countries, and we judge that we have insufficient data to conclude whether or not the developing countries have experienced benefits from spending on IT capital.

These results broadly conform to the earlier country-level studies performed by Dewan and Kraemer and Pohjola. Table 13 provides a comparison of the elasticity estimates from the developed-country subsample of this study to those given in the earlier papers, and it is evident that the details of the findings vary substantially even though the general interpretations are similar; indeed, our estimate of the output elasticity of IT capital falls about midway between the lower Dewan and Kraemer estimate and the higher Pohjola estimate. However, we find that the elasticity of IT capital is higher than that of non-IT capital, while Dewan and Kraemer found the opposite to be true. Several factors may account for this difference.

1. The Dewan and Kraemer study covered an earlier time period than this research, and the data were obtained from a different source.
2. The Dewan and Kraemer paper utilized econometric techniques to impute a level of capital stock, while this research used the Solow model to implicitly derive the production-function parameters.

3. The Dewan and Kraemer study did not control for differing levels of human capital, while the use of sector-level data allowed us to control for variations in labor effectiveness without requiring a human-capital variable.

The final point can be appreciated through reference to the Mankiw, et al. and Pohjola papers, where proxy measures of human capital were employed to control for differences in labor effectiveness across countries. The particular proxy used was the share of the working-age population in secondary school, which presents difficulties in interpretation due to the unknown units of measure. Moreover, in the Pohjola paper the coefficient on the proxy was not statistically significant, raising concern as to its effectiveness as a control variable.

An important methodological difference between this research and the earlier studies is that we have taken the sector, rather than the country, to be the unit of analysis. As we have shown, controlling for labor effectiveness is less problematical when done across sectors than across countries, and we suggest that the use of U.S. labor productivity as a control provides a highly credible solution. Since we have obtained statistically significant and internally valid measures of elasticities for both non-IT and IT capital, and since our methodology also avoids some of the estimation steps involved in constructing IT capital stock variables, we suggest that the conclusions presented here should be considered along with those of the earlier papers in forming a composite picture of the international dimensions of returns to IT investments.

At a more general level, this paper offers support for studies that have found that the so-called productivity paradox may be explainable as a measurement problem, as suggested by Griliches (1994), and that our understanding of the payoffs to IT investment may be expected to improve as more data (such as that used in this study) becomes available for analysis. International-level studies such as this offer additional insights to bolster the results of firm-level and sector-level research, and suggest that IT capital represents an important and continuing source of productivity and return on investment.

The lack of a relationship between IT capital and productivity in developing countries is puzzling, however, and warrants further investigation—especially since these countries are increasing their rates of investment and international economic agencies are encouraging them to do so through advice, consulting and loans for IT projects (or other capital projects which include large IT components). As noted above, it is possible that data or model limitations are responsible for the apparent result, but there are also more fundamental possibilities. For example, capital spending in developing countries may be too small to have an impact on productivity, or these countries may lack an adequate level of complementary investments in such things as information infrastructure and education. Also, there may be learning effects, such that investments in IT do not pay off in countries that have not gained a requisite amount of experience and management expertise. The data available to this study is inadequate for distinguishing between these various possibilities, and it is suggested that further research should seek to illuminate these issues.

Figures and Tables

Table 1 Developed and developing countries

Developed	***Developing***
Australia	Argentina
Austria	Brazil
Belgium	Chile
Canada	Colombia
Denmark	Greece
Finland	India
France	Korea (Rep. of)
Germany	Mexico
Hong Kong	Philippines
Ireland	Poland
Israel	Portugal
Italy	Taiwan
Japan	Thailand
Netherlands	Turkey
New Zealand	Venezuela
Norway	
Spain	
Sweden	
Switzerland	
United Kingdom	
United States	

Table 2 UN versus IBM sector definitions

UN Sectors	***IBM Sectors***
Manufacturing	Manufacturing
Electricity, Gas, Water	Utilities
Trade, Restaurants, Hotels	Distribution
Transport, Storage, Communication	Telecommunications, Medical Travel, Transportation
Financing, Insurance, Real Estate, Business	Finance Insurance
Community, Social, Personal Services	Government Health Education

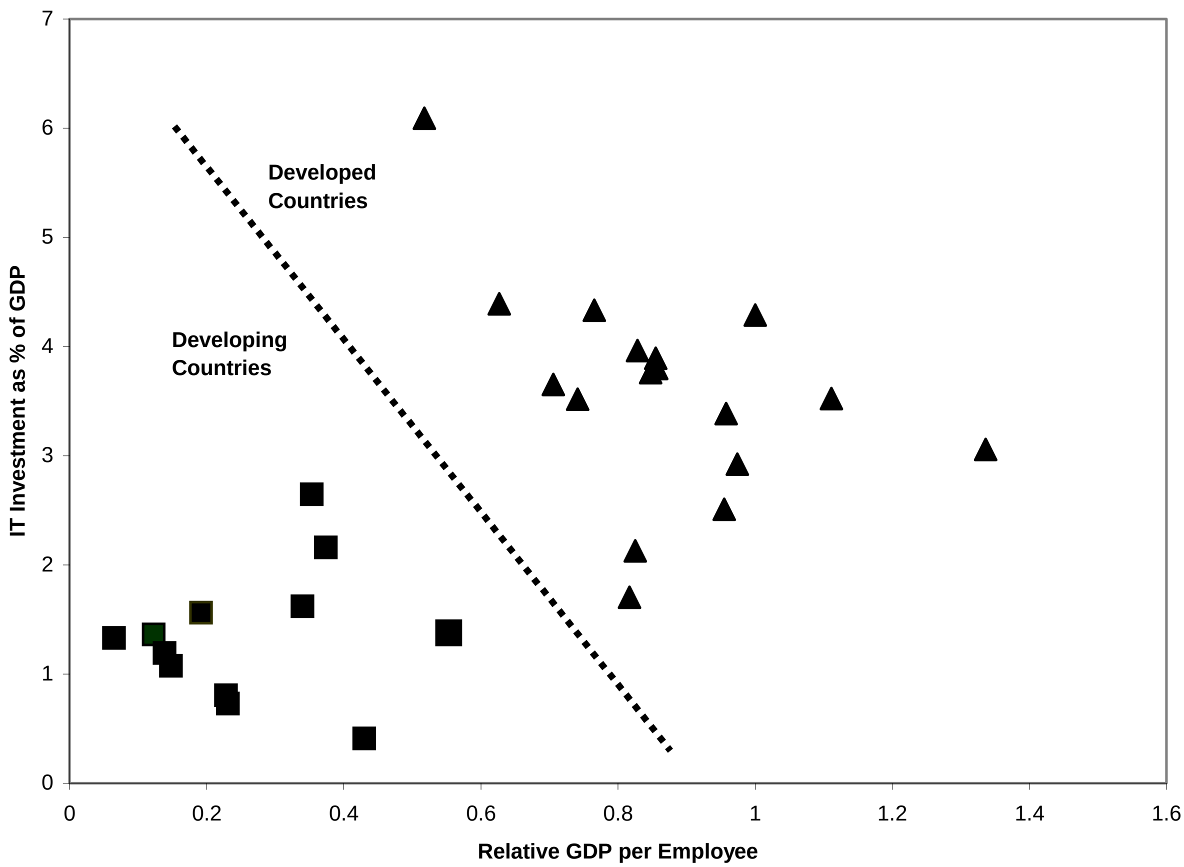


Figure 1 Division between developed and developing countries

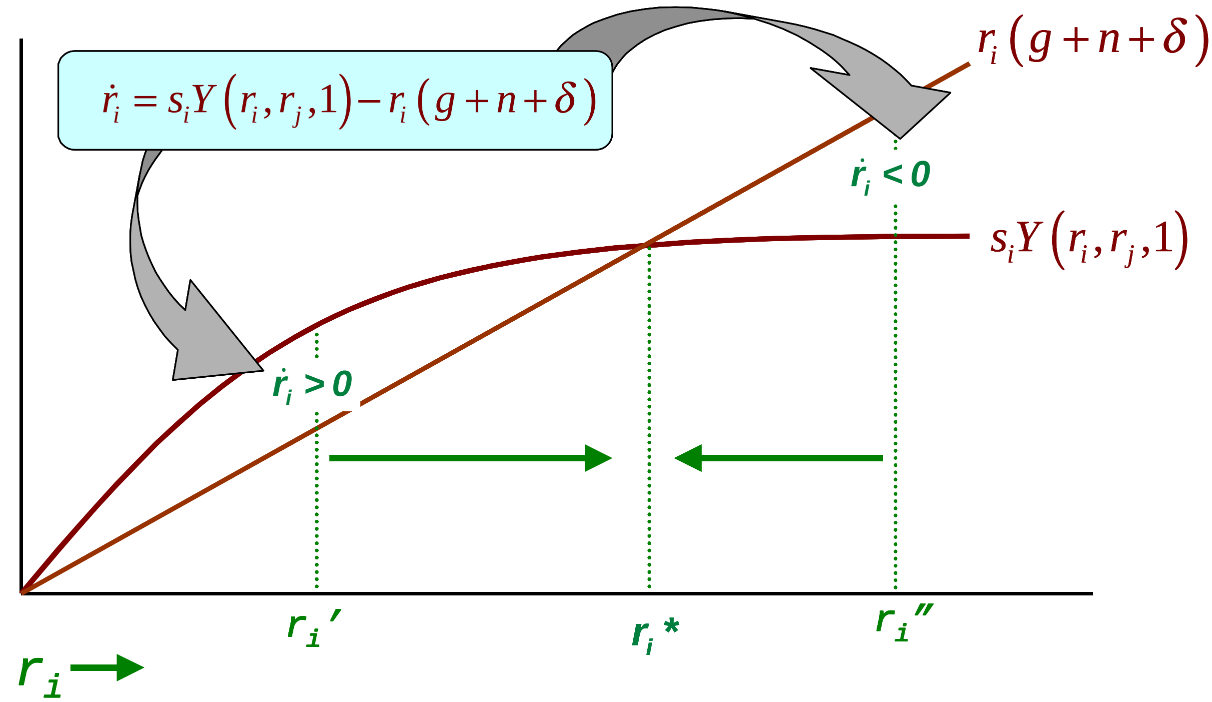


Figure 2 Solow growth model

Table 3 OLS estimation, unrestricted model

Method: OLS Fixed Effects
Observations: 12

Independent Variable	*Coefficient*	*Standard Error*	*t-Statistic*	*Significant p value*
ln v_1 (non-IT share)	0.1619	0.0893	1.8124	0.1128
ln v_2 (IT share)	0.2056	0.1597	1.2869	0.2391
ln $(n+g+\delta)$ (growth)	-0.1459	0.2116	-0.6898	0.5125
$C_{developed}$	0.4644			
$C_{developing}$	-0.4791			
Adjusted R^2	0.8974			
F statistic for restriction	0.5376			
p value for rejecting restriction	0.4821			

Table 4 FGLS estimation, unrestricted model

Method: FGLS, Fixed effects
Observations: 12
Iterations: 9

Independent Variable	*Coefficient*	*Standard Error*	*t-Statistic*	*Significant p value*
ln v_1 (non-IT share)	0.0813	0.0405	2.0092	0.0845
ln v_2 (IT share)	0.1511	0.0703	2.1495	0.0687
ln $(n+g+\delta)$ (growth)	-0.2377	0.0679	-3.5001	0.0100
$C_{developed}$	-0.1080			
$C_{developing}$	-1.0395			
Adjusted R^2	0.8816			
F statistic for restriction	0.0014			
p value for rejecting restriction	0.9713			

Table 5 FGLS estimation, restricted model

Method: FGLS, Fixed effects
Observations: 12
Iterations 9

Independent Variable	*Coefficient*	*Standard Error*	*t-Statistic*	*Significant p value*
ln v_1 (non-IT share)	0.0825	0.0237	3.4747	0.0084
ln v_2 (IT share)	0.1532	0.0356	4.3050	0.0026
$C_{developed}$	-0.0937			
$C_{developing}$	-1.0241			
Adjusted R^2	0.8968			

Table 6 Production-function parameters and factor shares

(1)	(2)	(3)	(4)	(5)	(6)
		IT conversion ratio: $\lambda_2 = 1$		IT conversion ratio: $\lambda_2 = 1.5$	
Type of capital	Elasticity (predicted share)	Actual share	Under-investment	Actual share	Under-investment
non-IT:	0.067	0.156	0.429	0.156	0.429
IT:	0.124	0.036	3.418	0.054	2.279
Total:	0.191	0.192	0.995	0.210	0.909

Table 7 Illustration of effects of μ and τ

Last year XYZ Corp bought an office accounting system for	$10,000		
This year they could buy the same system for	$6,000		
		μ:	0.4
Instead, they replace it with an ERP system with functionality multiple	2.5		
		τ:	0.4
And they pay (nominal spending)	$15,000		
This years purchase	$15,000		
x 1/ (1-μ)	2		
equals equivalent spending	$25,000		
x 1-τ	0.6		
equals real spending this year	$15,000		

Table 8 Effects of variations in $g + \delta$ and λ

		$g + \delta$								
		0.02	*0.03*	*0.04*	*0.05*	*0.06*	*0.07*	*0.08*	*0.09*	*0.1*
Unrestricted Regression Coefficients:	*non-IT*	0.078	0.082	0.082	0.082	0.081	0.081	0.081	0.080	0.080
	IT	0.178	0.166	0.159	0.154	0.151	0.149	0.147	0.145	0.144
	growth	-0.077	-0.122	-0.162	-0.200	-0.238	-0.275	-0.312	-0.348	-0.385
Test of restriction:	*F test*	2.635	1.094	0.386	0.072	0.001	0.092	0.291	0.562	0.878
	p level	0.139	0.323	0.550	0.795	0.971	0.768	0.602	0.473	0.373
Restricted Regression Coefficients:	*non-IT*	0.016	0.043	0.060	0.073	0.083	0.090	0.096	0.101	0.105
	IT	0.070	0.097	0.120	0.138	0.153	0.165	0.175	0.182	0.188
Implied Elasticities:	*non-IT*	0.015	0.038	0.051	0.060	0.067	0.072	0.076	0.079	0.081
	IT	0.064	0.085	0.101	0.114	0.124	0.132	0.138	0.142	0.146
Total capital share:		0.079	0.123	0.152	0.174	0.191	0.204	0.213	0.221	0.227
Under-Investment:	*non-IT*	0.096	0.243	0.326	0.386	0.429	0.462	0.487	0.506	0.521
	IT $\lambda = 1$	1.771	2.346	2.795	3.145	3.418	3.629	3.793	3.918	4.015
	IT $\lambda = 1.5$	1.181	1.564	1.863	2.097	2.279	2.420	2.528	2.612	2.676

Table 9 Marginal products

	Conversion ratio: λ =1	Conversion ratio: λ =1.5
non-IT:	0.04	0.04
IT:	0.28	0.19
Ratio IT/non-IT:	7.96	5.31

Table 10 Model estimation for developed-country subsample

Method: OLS, deviations form
Observations: 6

Independent Variable	*Coefficient*	*Standard Error*	*t-Statistic*	*Significant p value*
ln v_1 (non-IT share)	0.1075	0.0363	2.9590	0.0416
ln v_2 (IT share)	0.1931	0.0549	3.5158	0.0245
c	-0.0963			
Adjusted R^2	0.7982			

Table 11 IT underinvestment in developed countries

Type of capital	Elasticity (predicted share)	Actual share	Under-investment
non-IT	0.083	0.144	0.572
IT	0.148	0.038	3.948
Total	0.231	0.182	1.270

Table 12 Model estimation for developing-country subsample

Method: OLS deviations form
Observations: 6

Independent Variable	*Coefficient*	*Standard Error*	*t-Statistic*	*Significant p value*
ln v_1 (non-IT share)	0.1735	0.1446	1.1999	0.2964
ln v_2 (IT share)	-0.0042	0.2294	-0.0181	0.9864
c	-1.1422			
Adjusted R^2	0.0851			

Table 13 Comparison of elasticity estimates, developed countries

Study:	Table 11	Dewan&Kraemer	Pohjola
Years:	1991-1996	1985-1993	1989-1995
Elasticities			
non-IT:	0.08	0.16	
IT:	0.15	0.06	0.21
Physical:			0.26

References:

Barua, A., Kriebel, C.H. and Mukhopadhyay, T. "Information Technologies and Business Value: An Analytic and Empirical Investigation," *Information Systems Research* (6: 1), March 1995, pp. 3-23.

Brynjolfsson, E. and Hitt, L. "Paradox Lost? Firm-Level Evidence on the Returns to Information Systems Spending," *Management Science* (42: 4), April 1996, pp. 541-558.

Council of Economic Advisors *The Annual of the Council of Economic Advisors*, U.S. Government Printing Office, Washington, DC, 2001.

David, P.A. "The Dynamo and the Computer: An Historical Perspective on the Modern Productivity Paradox," *American Economic Review* (80: 2), May 1990, pp. 355-361.

Dewan, S. and Kraemer, K.L. "Information Technology and Productivity: Evidence from Country-Level Data," *Management Science* (46: 4), April 2000, pp. 548-562.

Dewan, S. and Min, C. "The Substitution of Information Technology for Other Factors of Production: A Firm Level Analysis," *Management Science* (43: 12), December 1997, pp. 1660-1675.

Greene, W.H. *Econometric Analysis, Third Edition*, Prentice Hall, Upper Saddle River, New Jersey, 1997.

Griliches, Z. "Productivity, R&D, and the Data Contstraint," *American Economic Review* (84: 1), March 1994, pp. 1-23.

Gurbaxani, V., Melville, N. and Kraemer, K.L. "Disaggregating the Return to IT Capital," Proceedings of the International Conference on Information Systems ICIS, Helsinki, Finland, 1998.

Jorgenson, D.W., Stiroh, K.J., Gordon, R.J. and Sichel, D.E. "Raising the speed limit: U.S. economic growth in the information age / Comments / Discussion," *Brookings Papers on Economic Activity 1* 2000, pp. 125-235.

Lehr, B. and Lichtenberg, F. "Information Technology and its Impact on Productivity: Firm-Level Evidence from Government and Private Data Sources, 1977-1993," *Canadian Journal of Economics* (32: 2), April 1999, pp. 335-362.

Lichtenberg, F. "The Output Contributions of Computer Equipment and Personnel: A Firm-Level Analysis," NBER, Cambridge, MA, 1993.

Loveman, G. W. "An Assessment of the Productivity Impact of Information Technologies," in *Information Technology and the Corporation of the 1990s: Research Studies*, T.J. Allen and M.S. Scott Morton (eds.), Oxford University Press, 1994, pp. 84-110.

Mankiw, N.G., Romer, D. and Weil, D.N. "A Contribution to the Empirics of Economic Growth," *Quarterly Journal of Economics* (107: 2), May 1992, pp. 407-437.

Mas-Colell, A., Whinston, M.D. and Green, J.R. *Microeconomic Theory,* Oxford University Press, New York, 1995.

Morrison, C.J. and Berndt, E.R. "Assessing the Productivity of Information Technology Equipment in U.S. Manufacturing Industries," NBER, Cambridge, MA, 1991.

Oliner, S.D. and Sichel, D.E. "Computers and Output Growth Revisited: How Big is the Puzzle?," *Brookings Papers on Economic Activity 2* 1994, pp. 273-333.

Oliner, S.D. and Sichel, D.E. "The Resurgence of Growth in the Late 1990s: Is Information Technology the Story?," Federal Reserve Board, Washington, DC, 2000.

Parks, R.W. "Efficient Estimation of a System of Regression Equations When Disturbances Are Both Serially and Contemporaneously Correlated," *Journal of the American Statistical Association* (62: 318), June 1967, pp. 500-509.

Pohjola, M. "Information Technology and Economic Growth: A Cross-Country Analysis," in *Information Technology, Productivity, and Economic Growth: International Evidence and Implications for Economic Development*, M. Pohjola (ed.), Oxford University Press, Oxford, 2001.

Roach, S.S. "White-Collar Productivity: A Glimmer of Hope?," Morgan Stanley, New York, 1988.

Schreyer, P. "The Contribution of Information and Communication Technology to Output Growth: A Study of the G7 Countries," OECD, STI Working Paper 2000/2, 2000.

Solow, R.M. "A Contribution to the Theory of Economic Growth," *Quarterly Journal of Economics* (70: 1), February 1956, pp. 65-94.

United Nations "National Accounts Data Description," Statistics Division, Economic Statistics Branch, 1999.