Information Technology and Productivity: Evidence from Country-Level Data

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This paper studies a key driver of the demand for the products and services of the global IT industry—returns from IT investments. We estimate an intercountry production function relating IT and non-IT inputs to GDP output, on panel data from 36 countries over the 1985–1993 period. We find significant differences between developed and developing countries with respect to their structure of returns from capital investments. For the developed countries in the sample, returns from IT capital investments are estimated to be positive and significant, while returns from non-IT capital investments are not commensurate with relative factor shares. The situation is reversed for the developing countries subsample, where returns from non-IT capital are quite substantial, but those from IT capital investments are not statistically significant. We estimate output growth contributions of IT and non-IT capital and discuss the contrasting policy implications for capital investment by developed and developing economies.
(*Information Technology*; *International*; *Productivity Paradox*; *Capital Investment*; *Information Technology Investment*)

1. Introduction

The global IT industry is large and growing rapidly. As shown in Table 1, the total revenues paid to vendors of computer hardware, software, communications, and services—the four components of "IT" in this paper—have grown from $162 billion in 1985 to $630 billion in 1996 and are projected to expand to $937 billion by the year 2000 (IDC 1997). The growth of IT spending is of special importance to the United States, where the combined output of computers and peripherals, microelectronics, and electronic components has surpassed the auto industry as the largest manufacturing sector (DOC 1998).[1] It is estimated that some 70% of global revenues for computer hardware, software, and services is from vendors headquartered in North America, most of which are U.S. companies (McKinsey and Company 1996). The demand for the products and services of the IT industry—U.S. and international—is ultimately influenced by the economic contributions of IT to the output and productivity of nations worldwide, which is the subject of empirical analysis in this paper.

The economic contributions of technology in general, and IT in particular, have important policy implications and have attracted the attention of researchers and policy analysts alike (see, e.g., Evenson and Ranis 1990, De Long and Summers 1991, Rosenberg et al. 1992). Organizations like the United Nations Development Program (UNDP) and the World Bank have provided significant funding for IT in developing countries. Hanna and Schware (1990) reported that

[1] It is estimated that by 1998, the value of shipments of information technologies (computer equipment, microelectronics, and electronic components) in the United States would be $355 billion, as compared to $227 billion for motor vehicles (DOC 1998).

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Table 1 Global IT Industry: Total Estimated Revenues Paid to Vendors of Computer Hardware, Software, Communications, and Services over 1985–1996 in Billions of Current U.S. Dollars (IDC 1997) and a Forecast for the Year 2000

Market	1985	1990	1991	1992	1992	1994	1995	1996	*2000*
Worldwide	162	367	390	417	432	473	557	630	*937*
United States	90	132	138	153	175	193	224	253	*385*
Japan	15	63	70	70	75	78	97	112	*155*
Europe	38	125	131	138	123	131	155	168	*221*
Asia Pacific (Ex. Japan)	8	18	19	21	24	30	38	47	*91*
Americas (Ex. U.S.)	7	18	21	23	23	26	30	34	*59*
Rest of the World	4	18	18	18	20	25	24	29	*44*

the World Bank currently spends $1 billion annually in grants and loans for IT projects in developing countries, and the volume of World Bank lending for IT was growing at an average annual rate of around 30%. There is a lack of hard empirical evidence both to inform these lending decisions and, more generally, to guide IT and non-IT capital investments by developed and developing economies. The analysis and findings of this paper will, we hope, narrow this gap.

Our research design is based on the estimation of an intercountry aggregate production function that relates GDP output to IT and non-IT inputs, using data from 36 countries over the period 1985–1993. Our analysis deals with new issues that are uniquely addressed with country-level data, and it complements previous research on IT and productivity. Key research questions that motivate this work are: What is the *international* experience with returns from IT investments? How do returns from IT capital investments differ from those from non-IT capital investments? Are there systematic differences between developed and developing economies with respect to the structure of their returns from capital investments?

This research is related to the "productivity paradox" of IT, which questions the contributions of IT to economy-level productivity and growth (see, e.g., Solow 1987, Roach 1991, Brynjolfsson 1993) and has generated recent research interest. One stream of research has analyzed firm-level U.S. data and found evidence of positive and significant returns from IT capital investment (see, e.g., Brynjolfsson and Hitt 1996, Lichtenberg 1995, Dewan and Min 1997). The merit of the firm-level approach is that it allows better measurement of IT contributions to quality and variety of output, which might be masked at higher levels of aggregation. However, the external validity of this research is debatable. It is an open question as to whether the findings are idiosyncratic of the largest U.S. corporations, or whether IT is helping to make the global "economic pie" bigger. Another stream of research has examined economy-level time series data to quantify the contribution of IT toward output growth of a single country, such as the United States or Singapore (Lau and Tokutsu 1992, Oliner and Sichel 1994, Wong 1994, Sichel 1997), with mixed findings on the contributions of IT. A problem with this approach is that the long time series of data required for statistical significance is not easily and consistently available for a relatively new technology such as computers. Further, capital and labor inputs for a single country tend to move together, with each other and with the scale of the economy, making it difficult to obtain robust results.

In contrast to previous research, our analysis is based on data from a cross section of countries over time. The benefits of our approach are: (1) direct focus on the economy level where productivity issues are more relevant—firms care more about profitability than productivity; (2) inclusion of total national inputs and outputs rather than a subset, as in the firm-level studies cited above; (3) prospects for greater variation in inputs and output that facilitate higher statistical significance; and (4) the ability to deal with new issues that are uniquely addressed with international country-level data.

Our findings suggest significant differences between developed and developing countries with respect to the structure of returns from IT and non-IT capital investments. We estimate that new IT capital investment accounts for as much as 53% of the annual GDP growth of the developed countries, while non-IT capital, with almost 20 times the IT factor share, accounts for just 15% of GDP growth. This is possibly because the developed countries have already built up mature capital stocks, and new growth opportunities have shifted in favor of IT-related assets. By contrast, we estimate that non-IT capital investments account for as much as 49% of the GDP growth of the developing countries in our sample, while the contributions of IT capital are not statistically significant. Perhaps a substantive base of capital stock and infrastructure is a prerequisite for IT investments to be productive. Developed countries have already made complementary investments in infrastructure, human capital, and information-oriented business processes, which can be leveraged by new IT investments for higher payoff. Our contrasting findings for developed and developing countries raise the possibility of "experience curves", wherein the path of economic development involves the building of overall capital stocks before IT-related capital investments become productive.

The rest of the paper is organized as follows. Section 2 presents the economic production framework and develops our empirical model. Section 3 describes our data set and the construction of variables. Section 4 describes our empirical findings and checks their robustness to various data and econometric issues. Finally, §5 offers some discussion and conclusions.

2. Production Function Framework

We consider an intercountry production function, having the form $Q_{it} = F(IT_{it}, K_{it}, L_{it}; i, t)$, where for Country $i = 1, 2, \ldots, N$ in Year $t = 1, 2, \ldots, T$, the output Q_{it} is annual GDP, and the inputs are: IT capital stock IT_{it}, non-IT capital stock K_{it}, and annual labor hours employed L_{it}. Our data set includes panel data for 36 countries over the period 1985 through 1993 (i.e., $N = 36$, $T = 9$). The symbols i and t following the colon indicate suitable controls for country- and year-specific effects, as described below.

For the functional form of $F(\cdot)$, we adopt the widely used Cobb-Douglas production function. Applying the Cobb-Douglas production function, we obtain for Country i ($i = 1, 2, \ldots, N$) in Year t ($t = 1, 2, \ldots, T$):

$$\log Q_{it} = \alpha + \lambda_t + \beta_{IT} \log IT_{it} + \beta_K \log K_{it} + \beta_L \log L_{it} + \nu_i + \epsilon_{it}, \tag{1}$$

where λ_t is a time effect captured by year dummy variables in the regression, ν_i is a country-specific effect invariant over time, and ϵ_{it} is the random error term in the equation, representing the net influence of all unmeasured factors. The Cobb-Douglas functional form can be viewed as a linear approximation of the actual underlying production function. It has been shown to be a good approximation in the IT and productivity context by Dewan and Min (1997),[2] and it is pervasive in the productivity research literature (see, e.g., Griliches 1998 for applications in R&D and productivity research). The focus of our analysis is on the estimation and interpretation of the output elasticities β_{IT}, β_K, and β_L, which measure the increase in output associated with a small increase in the corresponding input. For example, the output elasticity of IT capital, β_{IT}, represents the average percentage increase in annual GDP associated with a 1% increase in IT capital stock. The other elasticity parameters have analogous interpretations.

Our empirical analysis takes into account differences among the countries and changes over time. While the pooling of data from several countries increases the range of variation in the variables, and is therefore appealing on statistical grounds, it is crucial to properly account for country effects. Countries are likely to systematically differ in terms of weather, infrastructure, definition of inputs, productive efficiencies, and the like. In broad terms, there are two types of models for capturing cross-sectional heterogeneity: fixed effects models and random effects mod-

[2] Dewan and Min (1997) jointly estimate output and substitution elasticities in a firm-level analysis of IT and productivity, and they find that the translog and CES-translog production functions yield estimates of output elasticity that are virtually identical to those obtained from the Cobb-Douglas production function. Further, elasticities of substitution between IT and non-IT inputs are estimated to be very close to unity, consistent with the Cobb-Douglas model.

els (see, e.g., Greene 1990); we discuss each in turn as they apply to our problem.

In a fixed effects model, country-specific effects ν_i are represented by dummy variables in the regression, one for each country in the sample. In practice, however, we can avoid having to deal with a large number of dummy variables by transforming the variables in Equation (1) as deviations from country means. This transformation eliminates the country effects ν_i leading to the so called *within-countries* regression

$$\begin{aligned}\log Q_{it} - \log Q_{i.} &= \beta_{IT}(\log IT_{it} - \log IT_{i.}) + \beta_K(\log K_{it} - \log K_{i.}) \\ &\quad + \beta_L(\log L_{it} - \log L_{i.}) + \epsilon_{it} - \epsilon_{i.}, \end{aligned} \tag{2}$$

where we have suppressed the year dummies and used the notation $\log X_{i.} = 1/T \cdot \Sigma_{t=1}^{T} \log X_{it}$, for inputs $X = IT, K, L$, and $\epsilon_{i.} = 1/T \cdot \Sigma_{t=1}^{T} \epsilon_{it}$. The within-countries regression, estimated by ordinary least squares (OLS), is equivalent to the least squares dummy variables approach (see, e.g., Greene 1990).

In a random effects specification, country effects are characterized by a time-invariant component ν_i of the composite error term $w_{it} = \nu_i + \epsilon_{it}$. The component ν_i is the random disturbance characterizing Country i and it is constant through time. These country-specific error components are assumed to be randomly distributed across the cross section of countries. Using the random effects model, Equation (1) is estimated by generalized least squares (GLS), to take into account the nonspherical error structure under this specification.

This brings us to the question of whether to use fixed or random effects. Conceptually, we would like to make general inferences about IT and country-level productivity that are not conditioned on the specific composition of our data set. This favors a random effects model, especially because our sample is not exhaustive of the countries in the world. On the other hand, our sample is not altogether random, being more representative of the largest economies. Thus, institutional and data characteristics do not provide unequivocal guidance.

From a practical point of view, the dummy variables (fixed effects) approach is very costly in terms of the degrees of freedom lost, N in number. This makes the random effects model appealing, especially given the modest dimensions of our data set. Further, none of the desirable properties of the random effects estimators require T going to infinity, where the fixed effects model does rely on T increasing for consistency (Greene 1990, p. 494). However, the random effects model requires the potentially restrictive assumption that the ν_i be uncorrelated with the regressors to avoid inconsistency. Fortunately, there are econometric tests designed to test the orthogonality of the country random effects with the explanatory variables, and these will help us choose between random and fixed effects in §4.

The regression models described so far center on the short-run contemporaneous relationship between inputs and output. One might wonder how the long-run effects, on output, of IT capital and other inputs differ from those in the short run. We examine this question by analyzing the cross-sectional variation in the variables, which tend to reflect long-run effects (see, e.g., Berndt 1991, p. 455). One approach is to estimate the *between-countries regression*, obtained by restating Equation (1) in terms of the country means:

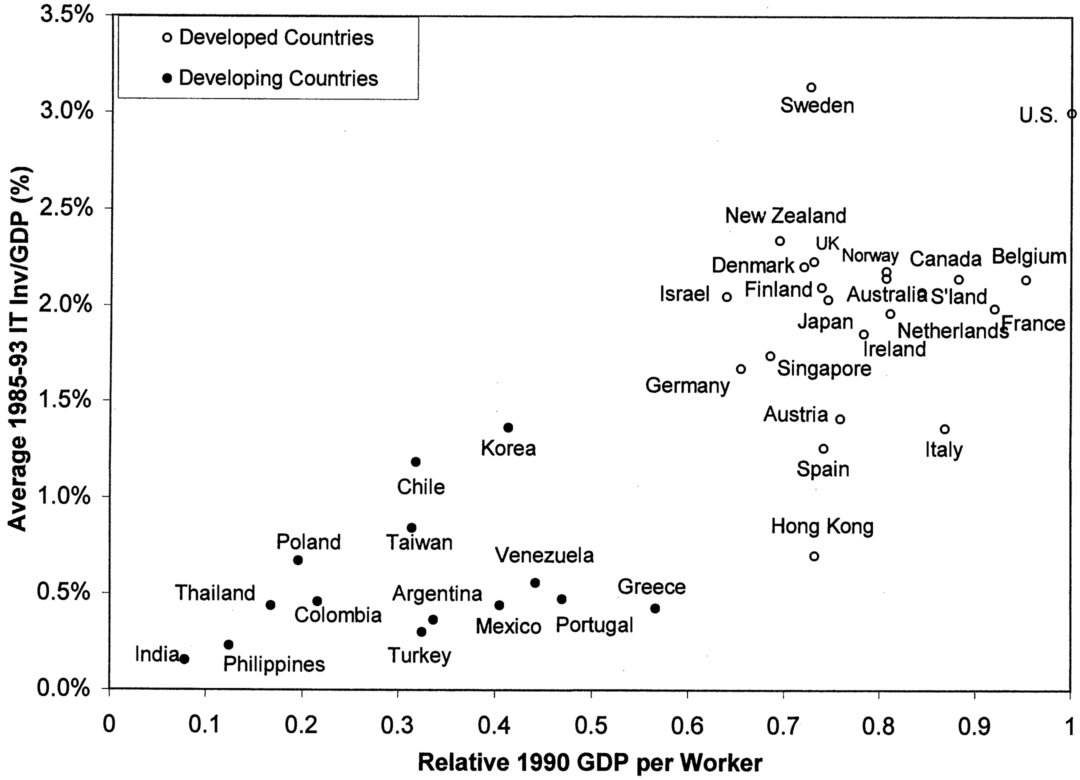
$$\begin{aligned}\log Q_{i.} &= \alpha + \beta_{IT} \log IT_{i.} + \beta_K \log K_{i.} \\ &\quad + \beta_L \log L_{i.} + \nu_i + \epsilon_{i.}. \end{aligned} \tag{3}$$

This regression is estimated by OLS, and the number of observations is clearly equal to the number of countries in the sample (or subsample). An alternative approach is to estimate the production function separately year by year, and then compare the elasticity estimates with each other and over time. Before estimating this and other regression models specified above, we describe the unique data set we have been able to assemble for this study.

3. Data and Variables

We start by describing the key IT capital stock variable, for which essential data were obtained from International Data Corporation (IDC). We obtained data on the value of IT shipments—the revenue paid to vendors (including channel markups) for hardware, data communications, software, and services—for 50

Figure 1 **Scatter Plot Between Average 1985–1993 Annual IT Investment as a Percentage of GDP Against Relative (to U.S.) 1990 GDP per Worker (Both Variables Measured in Terms of Constant 1990 International Dollars)**



countries, including the 36 used in our study (see Figure 1). Table 2 provides a detailed breakdown of the IT assets included in our measure of IT capital, classified into four categories: computer hardware, data communications, software, and services. The software series was adjusted for piracy using percentage of software piracy data from the Business Software Alliance and Software Publishers Association.

We first aggregated the four annual flow series into two broader categories: hardware and data communications (H&C) and software and services (S&S). H&C is converted from current dollars to constant 1990 dollars (and later to constant international dollars), using the Computers and Peripherals price index obtained from the U.S. Bureau of Economic Analysis. S&S is converted to constant 1990 dollars by assuming that the quality-adjusted average price of software and services declines at 5% annually, based on previous analysis by Gurbaxani (1990) and Sichel (1997). To obtain "seeding" values for the estimation of capital stock by the perpetual inventory method (see, e.g., Griliches 1998), the constant dollar H&C and S&S

Table 2 **Description of Assets Included in the IT Capital Measure by Asset Category**

IT Asset Categories	List of Assets
Computer Hardware	Personal computers, workstations, hosts, servers, storage devices, printers, other peripheral devices
Data Communications	Communications processors and controllers, LAN interfaces, concentrators, terminal servers, bridges, routers, modems, multiplexers, switching, and other equipment
Software	Packaged software, systems software and utilities, application tools, applications solutions
Services	Consulting services, implementation services, operational services, training and education, support services

investment flow series are extrapolated back to 1975, based on the price-adjusted S-curve growth models of Gurbaxani and Mendelson (1990), of which the Logistic model was found to provide the best fit in all cases.[3] H&C flows were aggregated into net stocks using depreciation profiles provided by the BEA that are based on work by Oliner (1993, 1994).[4] S&S flows were aggregated into net stocks assuming a three-year service life for the capitalized value of software and service expenses.[5] The H&C and S&S net stocks were added to yield the net stock of IT capital. It should be noted that our estimation of IT capital stock focuses only on "end use" computers and does not include embedded microelectronics (as in Lau and Tokutsu 1992) or telecommunications.

GDP and capital stock data are obtained from the Penn World Tables (PWT), where the portions relevant to us had been updated to 1993.[6] As described by Summers and Heston (1991), the PWT displays time series of national accounts variables denominated in real international dollars, based on detailed comparisons of benchmark international relative prices. The term "international dollars" refers to currency conversions based on purchasing power parities rather than exchange rates, so that *real* quantity comparisons can be made both across countries and time. Non-IT capital stock is calculated by subtracting H&C stock from the PWT capital stock figure.[7] Thus, we are able to calculate GDP, IT, and non-IT capital stock in constant 1990 international dollars using PWT data.

The labor input variable is measured in billions of worker hours. Total labor hours is calculated as the product of employment and the average number of work hours per year. Employment is the total number of workers, adjusted by the unemployment rate. Total number of workers was obtained from ILO Labor Statistics Database (ILO 1997) and World Bank (1997). Unemployment rates were compiled from IMF (1996), ILO (1997), and other national sources. The number of work hours per year was obtained from ILO (1997) and OECD (1997).

Figure 1 presents a scatter plot of the average 1985–1993 IT investment as a percentage of GDP against the relative (to U.S.) 1990 GDP per worker, where both variables are denominated in 1990 international dollars. There are a total of 36 countries whose IT investments as a percentage of GDP range from 0.15% in the case of India to 3.14% for Sweden. The median level of new IT investment is about 1.5% of annual GDP. It is clear from the figure that the countries sort out into two distinct clusters, which we have labeled "Developed Countries" and "Developing Countries." There is a substantial gap between the two groups in terms of the relative 1990 GDP per worker, with countries in the high GDP per worker cluster also tending to have higher levels of IT investment as a percentage of GDP. The wide gap between the two clusters should mitigate the possibility of selection bias resulting from misclassification of countries across the two categories (Mendelson 1987). It is natural to use the scatter plot of Figure 1 to categorize countries as developed or developing. We do consider alternative category definitions (see §4) to test the sensitivity of our results to subsample definition.

Summary statistics for the key variables are displayed in Table 3, separately for the full sample, and for the developed/developing countries subsamples. All dollar figures are stated in terms of constant 1990 international dollars. The average country in the full

[3] In the price-adjusted Logistic growth model, investment X_t in Year t (for X = H&C and S&S) is characterized by the equation $X_t = P_t^{-\alpha}/(K + Ab^t)$, where P_t is unit price of asset X in Year t, and K, A, b, α are model parameters that are estimated from the available investment time series (see Gurbaxani and Mendelson 1990 for details). The price indices P_t for H&C and S&S are as described in the text above.

[4] The overall depreciation rate for H&C, as a function of age, is calculated as an equally-weighted average of the depreciation rates for mainframes, PCs, and peripherals, where the last in turn is an equally-weighted average of the values for printers, displays, and storage devices.

[5] More specifically, the net stock of S&S in Year t is assumed to be equal to the sum of real S&S flows in Years $t-2$, $t-1$, and t.

[6] Version 5.6 is the last publicly available version of the Penn World Tables, originally released in 1995 with the variables updated to 1992. We were able to obtain GDP and capital stock data (in 1990 international dollars) for the period 1985–1993 directly from Professor Alan Heston, one of the PWT creators, prior to its general release to the research community.

[7] Actually, PWT contains capital stock *per worker*. To calculate capital stock itself we need to multiply the PWT number by the number of workers, which was estimated as explained in the text.

Table 3 Summary Statistics for the Full Sample and for the Developed/Developing Country Subsamples

Variable	All Countries		Developed Countries (DD Subsample)		Developing Countries (DG Subsample)	
	Mean	S.D.	Mean	S.D.	Mean	S.D.
GDP per Capita (I$)	11,954	5,675	15,880	2,938	5,786	2618
GDP (Billions I$)	488.7	939.6	626.1	1159.7	272.7	291.2
Labor Hours (Billions)	49.1	116.8	29.8	50.5	79.4	172.4
IT Capital as fraction of GDP	0.052	0.041	0.072	0.040	0.021	0.017
Non-IT Capital as fraction of GDP	1.233	0.454	1.378	0.478	1.004	0.294
Labor Cost as fraction of GDP	0.512	0.261	0.652	0.161	0.178	0.099

Note. Dollar figures are in terms of constant 1990 international (i.e., adjusted for purchasing power parity) dollars.

sample is quite large and rich, with a mean annual GDP of $488.7 billion international dollars and GDP per capita of $11,954. There is wide variation in country size, as evidenced by the fact that the standard deviation of GDP is roughly twice the mean. IT and non-IT capital stock, on average, constitute 5% and 123% of annual GDP, respectively; i.e., the factor share of non-IT capital is over 23 times that of IT capital. The average country employs roughly 50 billion labor hours annually.

The summary statistics for the developed and developing subsamples—labeled DD subsample and DG subsample, respectively—are quite different. Comparing the mean values of GDP and GDP per capita for the two subsamples, we see that the average developed country is more than double the size of the average developing country (in terms of GDP) and almost thrice as rich (in terms of GDP per capita). Developed countries have substantially higher IT intensity relative to developing countries: the factor share of IT capital is 7.2% for the DD subsample as compared to 2.1% for the DG subsample, on average. Finally, the average developing country employs more than double the number of labor hours, but labor cost as a percentage of GDP is less than a third, an indication of substantially lower real wage rates in the developing world.

4. Empirical Results

We now describe the results obtained by estimating the regression models described in §2. Table 4 presents the results obtained from the fixed and random effects specifications, applied to the full sample and the DD/DG subsamples.[8] Before discussing and interpreting the output elasticity estimates we address some model specification issues.

4.1. Specification Tests

Table 5 presents the results of various specification tests, with each row corresponding to a different null hypothesis. We start with the question of whether or not all countries are characterized by the same production function coefficients. Prior intercountry productivity research suggests significant differences between developed and developing countries (e.g., Lau and Yotopoulos 1989, De Long and Summers 1991). To test for the equality of coefficients across the two groups, we extend Equation (1) to include interaction terms between each of the production function variables—i.e., the three input variables and the year dummies—and a dummy variable that indicates whether the country in question is developed or not. The F Test reported in the first row of Table 5 indicates that the null hypothesis of equal coefficients for the DD and DG subsamples is rejected at the 1% significance level. Accordingly, throughout the rest of our

[8] Based on their large studentized residual values, the following set of influential observations were eliminated from both the fixed and random effects regressions: Argentina (1993), Germany (1991–93), Greece (1991), Mexico (1985), Poland (1991), Thailand (1986), Singapore (1985–87, 93), and Hong Kong (1985, 93).

Table 4 Production Function Estimates for the Full Sample and for the Developed/Developing Subsamples Based on the Fixed and Random Effects Models

	OLS Fixed Effects	GLS Random Effects
	All Countries	
β_{IT}	−0.013	−0.002
	(−1.269)	(−0.213)
β_K	0.492***	0.530***
	(13.216)	(14.828)
β_L	0.723***	0.494***
	(7.781)	(8.069)
DF	262	298
R^2	0.87	0.87
	Developed Countries	
β_{IT}	0.051***	0.057***
	(7.803)	(10.767)
β_K	0.176***	0.160***
	(3.256)	(3.227)
β_L	0.955***	0.823***
	(8.685)	(15.048)
DF	163	185
R^2	0.84	0.92
	Developing Countries	
β_{IT}	−0.015	−0.012
	(−0.951)	(−0.735)
β_K	0.578***	0.593***
	(10.755)	(11.256)
β_L	0.389***	0.277***
	(2.732)	(4.441)
DF	95	109
R^2	0.91	0.91

Note. t-statistics are in parentheses, and *** indicates significance at 1%.

analysis, we present separate estimates for the developed and developing subsamples only.

The second row in Table 5 indicates that year dummies are not statistically significant for the DD subsample, but they are significant for the full sample and for the DG subsample. This is not surprising because developing countries are undergoing rapid technological change as they continue to develop, while developed countries have advanced past the rapid growth phase. Based on these results, year dummies are omitted from regressions for developed countries below but are included in the regressions for developing countries.

The third row in Table 5 corresponds to a test of the statistical significance of country random effects, using the Lagrange Multiplier test, described in Greene (1990, p. 491). The null hypothesis is that the variance σ_ν^2 of the country-specific error component ν_i is equal to 0. The test statistic, calculated from the OLS residuals of the pooled regression (without country dummies), has a chi-squared distribution with one degree of freedom. The null hypothesis of zero variance is comfortably rejected at the 1% significance level for all three samples. This indicates that the random effects are statistically significant, and therefore a GLS estimation method is preferred to pooled OLS estimation.

Finally, we test the orthogonality of the country-specific error component ν_i with the explanatory variables, a condition that is necessary to avoid inconsistency that can result from omitted variables in the random effects specification. This test was devised by Hausman (1978) and is described in Greene (1990, p. 495). Under the null hypothesis of zero correlation between ν_i and the regressors, the test statistic is asymptotically distributed as chi-squared with K degrees of freedom, where K is the number of regressors. The results of this test, reported in the fourth row of Table 5, indicate that the null hypothesis of orthogonality is not rejected for any of the three samples. Accordingly, the GLS random effects model is preferred to the OLS fixed effects one.

4.2. IT-K Returns Structure

Based on the specification tests described above, we treat the GLS random effects model as our benchmark. Examining the GLS results for the full sample, note that the elasticities of non-IT capital and labor are positive and significant ($p < 0.01$ for both), but the IT coefficient is not statistically significant. The R^2 value indicates that the variables in the regression—the three input variables, year dummies, and an intercept term—together explain 87% of the variation in output. IT capital, however, is not correlated with output when all countries are pooled together in the regression. However, these results do not account for differences between de-

Table 5 Hypothesis Tests Regarding the Specification of the Production Function Regressions

	Test Statistic (p Value)		
Null Hypothesis	Full Sample	DD Subsample	DG Subsample
1. Production function coefficients for developed and developing countries are equal (F Test)	$F(11, 287) = 6.6$ ($p < 0.01$)	–	–
2. Year dummies are not significant (F Test)	$F(8, 298) = 1.9$ ($p = 0.057$)	$F(8, 177) = 1.0$ ($p = 0.43$)	$F(8, 109) = 2.1$ ($p = 0.04$)
3. Random effects are not significant (Lagrange Multiplier Test)	$\chi^2(1) = 18.5$ ($p < 0.01$)	$\chi^2(1) = 12.4$ ($p < 0.01$)	$\chi^2(1) = 7.9$ ($p < 0.01$)
4. Random effects are orthogonal to the regressors (Hausman's Test for Random vs. Fixed Effects)	$\chi^2(11) = 11.5$ ($p = 0.40$)	$\chi^2(11) = 2.3$ ($p = 0.51$)	$\chi^2(11) = 1.4$ ($p = 0.99$)

veloped and developing countries, which we have found to be significant.

For the DD subsample, all three input coefficients are estimated to be positive and significant ($p < 0.01$). The point estimate of IT elasticity is 0.057; i.e., a 1% increase in IT capital stock is associated with a 0.057% increase in average GDP output. The output elasticity estimates for non-IT capital and labor are 0.16 and 0.823, respectively, indicating slightly increasing returns to scale. Although non-IT capital has over 19 times the factor share of IT capital (see Table 3), the ratio of non-IT to IT output elasticity is just 2.8, suggesting that the returns from non-IT capital investment for developed countries are not commensurate with relative factor shares. In the case of the DG subsample, IT elasticity is statistically indistinguishable from 0, while the output elasticities of non-IT capital and labor are positive and significant ($p < 0.01$), with point estimates of 0.593 and 0.277, respectively, suggesting slightly decreasing returns to scale. Thus, non-IT capital investments appear to be quite productive, while IT capital investments are not correlated with higher average output of the developing countries in our sample.

The structure of returns from the two types of capital investments is strikingly different for the DD and DG subsamples. In particular, the *IT-K returns structure* is such that the DD subsample has a higher IT elasticity relative to the DG subsample, but a lower non-IT capital elasticity (despite a higher factor share of non-IT capital). Before discussing the implications of this returns structure, we assess its robustness to various data quality and specification issues, starting with the possibility of subsample selection bias.

For the purpose of checking robustness to subsample definition we consider two alternative groupings, the results for which are reported in Table 6. The first variation considers reduced DD/DG subsamples obtained by dropping "borderline" countries at the edge of their respective clusters in Figure 1—"DD Minus" is obtained by dropping Hong Kong and Israel from the DD subsample, and "DG Minus" is obtained by dropping Greece from the DG subsample. The second variation in Table 6 uses OECD member-

Table 6 Checking for Sample Selection Bias: Production Function Estimates Using Alternative Subsamples

	Developed Countries		Developing Countries	
	DD Minus	OECD	DG Minus	Non-OECD
β_{IT}	0.095***	0.051***	0.011	−0.012
	(7.792)	(10.482)	(0.703)	(−0.796)
β_K	0.017	0.229***	0.658***	0.587***
	(0.557)	(4.823)	(12.568)	(12.369)
β_L	0.901***	0.717***	0.259***	0.314***
	(28.940)	(14.560)	(3.519)	(5.178)
DF	169	180	101	107
R^2	0.99	0.92	0.93	0.93

Note. DD Minus is the DD subsample without Israel and Hong Kong; DG Minus is the DG subsample without Greece; OECD is the subsample of countries that are members of the OECD; Non-OECD is the subsample of countries that are not members of the OECD; t-statistics are in parentheses, and *** indicates significance at 1%.

ship as a proxy for economic development.[9] Comparing the results in Tables 4 and 6, note that the OECD-based subsamples yield roughly the same results as the original subsamples, while (not surprisingly) the reduced DD/DG subsamples demonstrate a sharper contrast between developed and developing countries. Overall, the IT-K returns structure appears to be quite robust to subsample selection.

Next, we consider the issue of errors in variables, which if serious enough can lead to biased and inconsistent estimates. In this regard, the IT capital variable is the most prone to error, especially because we had some latitude in its construction, which involved aggregation, extrapolation, and adjustments for software piracy. We examined the robustness of our results to three alternative proxies of the IT capital variable, which differed from the original variable in the following ways, respectively: (1) measurement of IT capital in terms of U.S. rather than international dollars; (2) no piracy adjustment for the software component; and (3) only hardware and communications are used to measure IT capital (not software and services). We found to our surprise that the results are remarkably insensitive to the alternative measures of IT capital for both the developed and developing subsamples. This is possibly because the various components of IT capital tend to be highly correlated with each other, and IT capital has (relatively) much higher variation than the other variables.

We also examined robustness to autocorrelation and simultaneity (see Table 7). For the former, we estimated the AR(1) model of Parks (1967), which allows for heteroskedasticity and contemporaneous correlation between cross sections, in addition to first-order autoregression. The parameter estimates are somewhat different from those in Table 4—especially IT elasticity for developed countries—but the overall pattern of results is similar. It is reasonable to conclude that the IT-K returns structure is robust to autocorrelation.

Table 7 Robustness Check for Autocorrelation and Simultaneity: Production Function Estimates for AR(1) and 2SLS Models

	Developed Countries		Developing Countries	
	AR(1)	2SLS	AR(1)	2SLS
β_{IT}	0.141***	0.055***	0.006	−0.013
	(41.990)	(6.948)	(0.542)	(−0.695)
β_K	0.259***	0.189***	0.551***	0.558***
	(7.747)	(3.082)	(15.326)	(9.376)
β_L	0.618***	0.951***	0.307***	0.288*
	(21.790)	(6.763)	(14.086)	(1.669)
DF	186	143	114	83
R^2	0.99	0.81	0.98	0.89

Note. In the 2SLS model, the labor variable was instrumented using one-year lagged values of the two endogenous variables (GDP and labor) and all other exogenous variables in the regression. *t*-statistics are in parentheses, and *** and * indicate significance at 1%, and 10%, respectively.

With respect to simultaneity (which manifests itself as a correlation between the regressors and the error term), the labor variable is the one that is most likely to be endogenous. Shocks in annual GDP are likely to trigger contemporaneous adjustments in aggregate labor employment levels. GDP and labor hours, being "flow" variables, are therefore likely to be jointly determined. By contrast, IT capital and non-IT capital are "stock" variables that are inherently less sensitive to immediate changes in GDP. To examine how our results change when labor is treated as an endogenous variable, we estimated the within regression of Equation (2) using two stage least squares (2SLS), instrumenting the labor variable. The set of instruments included one-year lagged values of the GDP and labor variables, plus all other exogenous variables (i.e., IT capital, non-IT capital, and year dummies). Note that the 2SLS estimates reported in Table 7 are not materially different from the corresponding OLS estimates in Table 4, indicating that simultaneity is not a serious problem here.

4.3. Growth Contributions of Capital Investments

We now apply our benchmark estimates of Table 4 to quantify the contributions of IT and non-IT capital

[9] The OECD—Organization for Economic Cooperation and Development—is an international organization of the most industrialized, market economy countries. The 22 OECD members in our data set are: Australia, Austria, Belgium, Canada, Denmark, Finland, France, Germany, Greece, Ireland, Italy, Japan, Netherlands, New Zealand, Norway, Portugal, Spain, Sweden, Switzerland, Turkey, United Kingdom, and United States. The remaining 14 countries in our data set were not OECD members during the sample period.

investment to GDP growth. Recall that IT output elasticity measures the percentage increase in GDP associated with a one percent increase in IT capital. Therefore, as a first-order approximation, the percentage GDP growth due to new IT investment can be estimated by multiplying the estimated IT output elasticity by the percent cumulative average annual growth rate (CAGR) of IT capital over the sample period. The growth contribution of non-IT capital is analogously estimated.

The CAGR of GDP over the sample period of 1985–1993 is 2.98% per year for the developed countries and 4.96% for the developing countries. The question is how much of this GDP growth rate is explained by growth in IT versus non-IT capital. Starting with developed countries, the CAGR of IT capital stock, averaged over the 22 developed countries in our sample, is equal to 27.77%. Accordingly, the percent GDP growth associated with growth in the IT capital stock of developed countries is equal to 27.77*0.057 = 1.58%, which is roughly 53% of the GDP growth rate of developed countries, on average. Similarly, because the average CAGR of non-IT capital for developed countries is 2.74%, we calculate that non-IT capital contributes 2.74*0.16 = 0.44% or about 15% of the GDP growth of these countries. For the developing countries in our sample, the average CAGR of non-IT capital stock is 4.1%. This implies that non-IT capital contributes 4.1*0.59 = 2.43%, which is 49% of the average GDP growth rate of these countries.

Along these lines, we can also estimate the contribution of IT capital to the growth rate of the United States—a developed country. For this purpose, we apply the IT elasticity estimate for the developed countries subsample to U.S. data. The CAGR of IT capital stock in the United States is equal to 21.17% over the sample period. Accordingly, we estimate that IT capital growth contributed 21.17*0.057 = 1.21% out of the total U.S. GDP growth of about 2.92% per year over this sample period. Thus, by our estimates, IT investment accounted for roughly 41% of U.S. GDP growth in the period 1985–1993. Analogously, we estimate that the growth of non-IT capital accounts for roughly 12% of the average annual GDP growth in the United States over the sample period.

4.4. Long-Run Cross-Sectional Effects

As explained in §2, we can get a sense for the long-run effects of IT capital on output by focusing on purely cross-sectional specifications. We start with the between-countries regression (Equation (3)), whose results are reported in Table 8. Comparing the results for the DD and DG subsamples, we see that the structure of returns on IT versus non-IT capital investment displays the same pattern as in the GLS results. The estimated IT elasticity for developed countries is substantially higher than that in the GLS regression, suggesting that IT appears to have a larger effect on output in the long run than in the short run.

Next, we estimate the production function year-by-year and report the results in Table 9. To account for correlations in error terms across years, we estimate using seemingly unrelated regression (SUR). To the extent that cross-sectional regressions reflect the longer term relationship between inputs and output, it is not surprising that most IT elasticity estimates are positive, except for developing countries during 1985–1988. Further, there is an increasing trend in IT elasticity, but a decreasing trend in non-IT capital elasticity, tracking the increasing relative real factor share of IT capital for all countries. There is evidence that IT investments have started to become productive for developing countries toward the end of the sample period. The time trend in the estimated coefficients should be interpreted with caution because of possible distortions induced by the deflators. In this regard, the estimates for the base year of 1990 are probably the

Table 8 **Production Function Estimates from the Between-Countries Regression for the Developed/Developing Country Subsamples**

	Developed Countries	Developing Countries
β_{IT}	0.212***	0.046
	(3.106)	(0.368)
β_K	0.080	0.670***
	(1.160)	(3.191)
β_L	0.734***	0.206
	(8.609)	(1.613)
DF	18	10
R^2	0.99	0.91

Note. *t*-statistics are in parentheses, and *** indicates significance at 1%.

Table 9 Year-by-Year Seemingly Unrelated Regression (SUR) for the Developed/Developing Country Subsamples

	1985	1986	1987	1988	1989	1990	1991	1992	1993
					Developed Countries				
β_{IT}	0.117**	0.112**	0.111***	0.100***	0.106***	0.114***	0.090**	0.082**	0.080*
	(2.669)	(2.652)	(2.947)	(2.926)	(3.333)	(3.693)	(2.751)	(2.252)	(1.975)
β_K	0.158**	0.111	0.083	0.080	0.087	0.084	0.071	0.053	0.058
	(2.164)	(1.577)	(1.305)	(1.344)	(1.573)	(1.555)	(1.286)	(0.897)	(1.059)
β_L	0.758***	0.812***	0.839***	0.855***	0.839***	0.826***	0.862***	0.888***	0.876***
	(8.813)	(9.937)	(11.455)	(12.421)	(12.991)	(13.407)	(13.929)	(13.269)	(13.076)
DF					162				
R^2					0.98				
					Developing Countries				
β_{IT}	0.003	−0.004	0.003	0.011	0.056**	0.077*	0.107*	0.154**	0.195***
	(0.125)	(−0.207)	(0.12)	(0.552)	(2.543)	(1.840)	(2.202)	(2.848)	(3.171)
β_K	0.676	0.690***	0.669***	0.631***	0.515***	0.434***	0.427***	0.390***	0.378***
	(7.988)	(8.703)	(8.277)	(8.493)	(7.167)	(4.479)	(4.052)	(3.743)	(3.379)
β_L	0.207	0.196**	0.215**	0.240***	0.305***	0.321***	0.303***	0.307***	0.308***
	(2.572)	(2.547)	(2.801)	(3.357)	(4.409)	(3.593)	(3.265)	(3.437)	(3.357)
DF					90				
R^2					0.95				

Note. DF (degrees of freedom) and R^2 are the system-wide values, *t*-statistics are in parentheses, and ***, **, * denote significance at 1%, 5%, and 10%, respectively.

most reliable, and they indicate a similar IT-K returns structure to our benchmark results of §4.2.

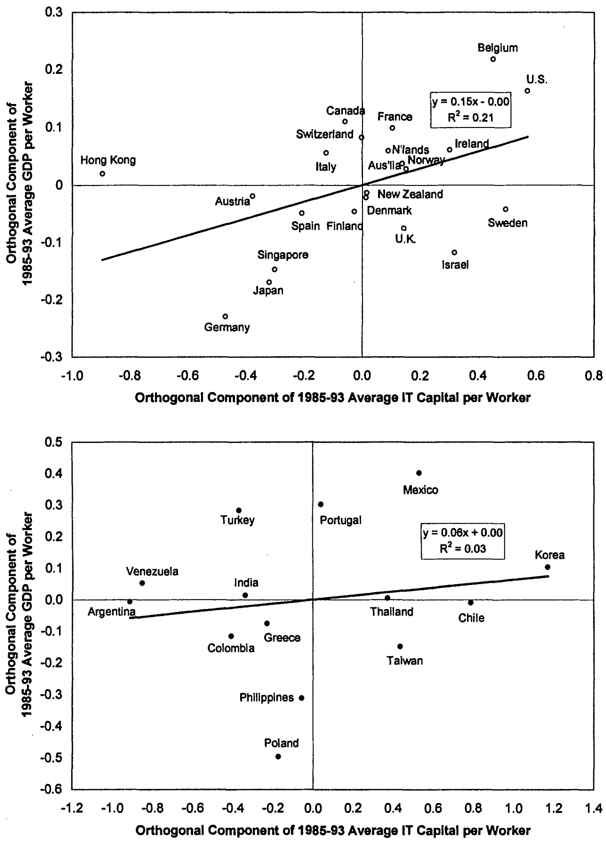
A somewhat different perspective on the cross-sectional effects is provided in Figure 2, which depicts the relationship between IT capital per worker and labor productivity, as measured by GDP per worker. The figure displays, separately for developed (top panel) and developing (bottom panel) countries, scatter plots between the orthogonal components of the average 1985–1993 GDP per worker and IT capital stock per worker, respectively. The orthogonal components measure the portions of the respective variables not explained by the variation in the control variables. More concretely, the orthogonal components are the residuals obtained by separately regressing the average GDP per worker and the average IT capital per worker against the two control variables. In effect, the trend lines illustrate the linear regression between GDP per worker and IT capital per worker, with non-IT capital per worker and the number of workers as additional regressors.

The trend lines in both figures slope upwards indicating that an increase in IT capital per worker is associated with an increase in labor productivity across the cross section of countries. Countries scattered above (below) the trend line have a higher average level of GDP per worker than that explained by the level of IT capital stock per worker. The equations of the trend lines, reported on the figures, indicate that both the slope and goodness of fit are higher in the case of the developed subsample as compared to the developing subsample. In particular, the level of IT per worker explains over 20% of the variation in GDP per worker across the cross section of developed countries, while it is practically unrelated to variation in labor productivity across the developing countries.

5. Discussion and Conclusions

The "productivity paradox" of IT is clearly an international phenomenon (Dewan and Kraemer 1998), yet the bulk of previous research on this subject is restricted to data from only the largest firms in the U.S.

Figure 2 **Relationship Between Orthogonal Component of the 1985–1993 Average GDP per Worker and Orthogonal Component of the Average IT Capital per Worker for Developed (top) and Developing (bottom) Countries**



private sector.[10] Accordingly, previous evidence of positive returns from IT investment leave open the question of external validity beyond the narrow domain of these studies. Are the results idiosyncratic to large U.S. corporations? Taking a more aggregate perspective, this paper studies the link between IT investment and productivity by estimating an intercountry production function on annual data from 36 countries over the 1985–1993 period. We are able to extend the evidence of positive IT returns to a broad set of developed countries, which includes the United States. Our results have differential policy implications for IT investments, depending on the level of economic development.

For developed countries, our results are consistent with the notion that these countries have already built up a mature stock of ordinary capital to support economic activity and, as a result, the marginal productivity of added non-IT capital investment is low. In contrast, our findings suggest that there is ample room for productive IT investment to take advantage of substantial returns at the margin. It is worth noting, however, that the estimated returns reflect not just IT capital investments, but other factors as well that tend to be correlated with IT investment. Thus, increasing levels of IT investment by developed economies over time have been accompanied by complementary investments in such factors as infrastructure and human capital, as well as a steady "informatization" of business models, all of which serve to enhance and amplify the effects of IT investments.

By the same token, one explanation for the insignificant estimated returns from IT investments in developing countries is the overall lack of the above IT-enhancing complementary factors in those economies.[11] Our results suggest that these countries might be better off focusing on more basic investments in overall capital stock, which in turn will serve to make other inputs more productive. This is reflected in the relatively high estimates of non-IT capital elasticity, but low values of IT capital and labor elasticity. However, the fact that our analysis does not find a measurable contribution of IT to the economies of developing countries does not necessarily mean that developing countries or development institutions should shy away from IT investments. On the contrary, it is possible that there are learning effects so that countries must accumulate a certain level of experience with information technologies before investments in this relatively new factor of production start to pay off. Also, perhaps these countries should prioritize

[10] Notable exceptions include Wong (1994), who studied data from three Pacific-Rim countries; Tam (1998), who analyzed data from Singapore; and Lehr and Lichtenberg (1998) whose study focuses on U.S. federal government agencies.

[11] We cannot rule out the alternative explanation that our regressions are simply not detecting IT effects for developing countries, due to the relatively low levels of IT capital stocks in these countries and/or noisy data.

their IT investments into longer term infrastructure projects rather than costly short-term IT applications.[12]

Compared to the advanced economies, less-developed countries have poorer infrastructure, inherently less productive human capital (in part due to lower levels of education) and business models that have yet to transition from the industrial to the information age (see, e.g., Kraemer and Dedrick 1994). The development literature suggests that the countries adopting new technology must have the right environmental conditions such as basic infrastructure, business practices, and appropriate government policies. Such policies include promotion of computer use, promotion of education generally and for computer professionals in particular, enactment of low taxes and tariffs on computer imports, and telecommunications liberalization to lower costs (Dedrick et al. 1995, Dedrick and Kraemer 1998, Kraemer et al. 1996).

Putting together our results for developed and developing countries raises the intriguing possibility of "experience curves" for capital investments, wherein economies must first build their ordinary capital stocks before investments in information technology become productive. Must they build selective stocks in telecommunications and human capital? Must they build IT stocks to some critical mass? Must they build IT, complementary assets, and other non-IT capital together? Clearly, answers to these questions require research beyond the scope of this paper. However, the notion that there might be experience curves is reflected in Rostow's (1990) analysis of the stages of economic growth, in which he argues that there are preconditions for takeoff from less developed to developed economies. In general, these preconditions include technology, social and human capital, along with infrastructure and policies. Future research should address the link between IT and these other preconditions required for faster economic growth.

From the perspective of the information industries, which is the focus of this special issue, the results of this analysis suggest that the demand for the products and services of the IT industry will continue to be strong given the positive returns from IT investments for the advanced economies. Moreover, developing countries can also be expected to grow their IT investments, especially in IT infrastructure, following the normal diffusion process of new technologies.

Finally, the distinctive contributions of this paper are worth noting. Our findings add to the evidence that there are positive returns on IT investment, expanding the scope of the evidence from the United States alone to a broad set of developed countries. To our knowledge, this is the only country-level analysis of the returns from IT investments ever conducted. Also, it is the first comparative analysis to explicitly incorporate IT as a factor of production along with traditional inputs of capital and labor into an intercountry production function. And, finally, it the first time that a rich database on a large number of countries has been assembled for such analyses. We expect that the database will support analysis of other issues such as the influence of environmental factors and national policy on the contributions of IT to economic output and productivity.[13]

[12] This is not unlike the finding of Dewan and Mendelson (1998) in the securities trading context, where IT-disadvantaged traders are better off channeling their IT investments into longer run IT infrastructure rather than short-run IT applications.

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