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Infrastructure and productivity: An extension to private infrastructure and it productivity

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Abstract

This paper incorporates both public and private infrastructure within the framework of a nonlinear production function. The theoretical model specifies a technological growth rate as a nonlinear function of government infrastructure and private infrastructure generated by the information sector of the economy—cable, wireless stations, satellites, internet facilities, broadcasting, etc. The time trend is included to capture the effect of all other variables. The empirical estimates generated by the model imply increasing returns to scale for the US economy in the last few years. The evaluation of the growth accounting equation implies that information technology was the largest contributing component to growth during the expansion of the 1990s.

JEL classification: C5; O4,

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One might say, "as productivity goes, so goes the standard of living". No wonder that over a span of three decades economists have been preoccupied with analyzing the fluctuations in US productivity growth. During that time period the US experienced a productivity slowdown starting in the early 1970s (coincident with sharply increased energy prices), and a productivity revival that began sometime in the mid 1990s. In a previous paper (Journal of Econometrics, 1999), we identified public infrastructure as a major determinant of productivity during the 1970s and 1980s. That exploration, using a

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data set that ended in 1989, had significant macro policy implications. However, it became clear to us by 1997, when that paper was submitted for publication, that a different type of infrastructure would play an increasingly important role in productivity analysis. In the concluding remarks of our paper we refer to this as the information super highway.

> ''By using a core definition of infrastructure, this study has only scratched the surface of infrastructure's total contribution to productivity gains. As the information super highway becomes a reality, cutting infrastructure does not appear to be a wise decision. Even though much of the investment in the information sector is private, it depends strongly on public licensing, regulation, and support in being a 'common carrier' that serves industry and the population at large, just as infrastructure, in the broad sense, is supposed to do.''[1]

We can see the effects of productivity growth in the statistics of output per unit of various types of input, and in the indirect results of a lengthy and strong economic expansion, without an upsurge of inflation. Moreover, even as the US economy slipped into recession in 2001, worker productivity estimates remained resilient. Thinking has radically changed regarding the unemployment rate, at full-employment, and the US potential growth rate.

As the information super highway did in fact become a reality, many economists began to look for explanations by focusing on the contribution of information technology (IT) capital stock to productivity growth. This IT capital consists of information equipment (hardware), information software (human capital), and telecommunications that includes economy-wide cable, wireless stations, satellites, internet facilities, broadcasting, etc., Oliner and Sichel (2002) report that by 2000 the consensus view was that a productivity revival had started in 1995, and was linked to the increasing investment in IT capital throughout the economy.

The growing body of research that supports this consensus view identifies two significant themes that are central to the analysis. First, it is important to account for substitution between different types of capital, given the steady relative price decline of IT assets (Harchaoui et al., 2002; McGuckin and Stiroh, 2000; Stiroh, 2002a, b). This substitution leads to a compositional change in the capital stock that has been referred to as growth in capital quality (Harchaoui et al., 2002; Stiroh, 2002a, b; Jorgenson et al., 2002; Jorgenson and Stiroh, 1999). Such a compositional change would be illustrated by an upward shift in the production function, just as any shift generated by an increase in the technological index.

Second, the productive impact of IT capital is not limited to its use as a factor input. As far back as the mid 1980s, Leff (1984) hypothesized that the major impact of IT capital would come from its role in creating an information infrastructure that reduces transaction costs and increases organizational efficiency. Hicks and Nivin (1998) report for the US that by 1991 there were 1.65 million networked systems valued at approximately \$101 billion in 826,000 sites. This IT infrastructure consists of multi-user computer networks and integrated telecommunications systems. As a result, the spillover effects produced by the creation of this infrastructure cause IT capital to become a source of total factor productivity (TFP) growth.[2]

[1]Duggal, V.G., Saltzman, C., Klein, L.R. (1999). Infrastructure and productivity: a nonlinear approach, Journal of Econometrics 92, p. 72.

[2]Total factor productivity refers to technological progress that increases output for a fixed level of factor inputs. It is often referred to as the Solow residual, and considered to be the result of exogenous, or disembodied

The direct implications of these spillover effects are that IT capital is not necessarily subject to diminishing marginal productivity over the entire range of feasible values, nor is the production function limited by constant returns to scale. Additionally, the identification of IT capital as a contributing component to TFP means that there is an aspect of technological progress that is endogenous.[3] Moreover, there are indications that technological progress that results from investment in IT capital may not be neutral in its impact on the marginal productivities of non-IT capital and labor. Discussions in the literature clearly point to a potential bias in its impact on the marginal product of labor, with the possibility of a lagged effect due to adjustment costs associated with the learning effect (Dedrick et al., 2003; Kiley, 2001). This bias is attributed to improved information flows that allow labor to make decisions more effectively and lower the costs of coordinating economic activity.

In reviewing the available literature on the impact of IT on productivity, it becomes apparent that for the US there have not been any empirical studies, at the aggregate level, that use macro gross domestic product data as the dependent variable, and span a time period that includes the 1970s and the 1990s. Empirical work conducted in the 1980s, at the aggregate level, did not find a statistically significant link between investment in IT capital and productivity (Roach, 1987; Morrison and Berndt, 1991). These findings resulted in the often cited "productivity paradox" discussion in the early literature (Sichel, 1999; Triplett, 1999). More recent aggregate studies have put the productivity paradox to rest; however, they have used growth accounting calculations as the basis of their conclusions (Oliner and Sichel, 2002; Jorgenson and Stiroh, 1999; Harchaoui et al., 2002). In making these calculations, perfect competition and constant returns to scale are assumed so that factor shares can be used to proxy output elasticities. In the words of Stiroh (2002): "This essentially assumes that there is a productive impact of IT investment, so it is critical to also econometrically test for a link between IT use and productivity gains."[4] Given that economic policy decisions are so often macro in nature, this lack of empirical work at the aggregate level leaves a visible void in the literature.

It is our belief that researchers need to go back directly to production function analysis, an area that played an extremely large role in the development of 20th Century econometrics inspired by the work of Paul Douglas. However, in developing the production function specification, it is essential to accommodate all of the roles performed by IT capital in its contribution to productivity. This requires a function that does not restrict production to constant returns to scale, diminishing marginal productivity, or exogenous technological change.

In this paper we aim to add to the literature by estimating an aggregative production function for non-residential, non-farm output in the US economy in order to quantify statistically the component contribution of IT capital to GDP growth. Particular attention is paid to the aggregation issues spawned by the BEA's introduction of chain-weighted

(*footnote continued*)
technological progress. Econometric studies generally account for the impact of exogenous technological change by including time as an explanatory variable in the structural equation to be estimated. Some economists refer to total factor productivity as multi factor productivity (MFP) e.g., Dedrick et al., (2003), Oliner and Sichel (2002).

[3]For a more complete discussion of IT's impact on TFP, and its relation to endogenous growth theory see Dedrick et al., (2003).

[4]Stiroh, K.J. (2002). Information technology and the U.S. productivity revival: a review of the evidence, Business Economics 37, p. 34.

indexes in 1996.[5] Specifically, chain-weighted real GDP is not additive in its underlying components. The BEA has developed chained-dollar estimates of the component contributions by multiplying the chained-dollar indexes by the current-dollar values of a specific reference year (Landefeld et al., 2003). This method produces reasonable approximations for component contributions of goods and services whose percentage price change is close to the overall rate of inflation. This, however, is not the case for computers, software and telecommunications equipment, all of which have experienced rapid growth in real sales accompanied by falling relative prices. Under such circumstances, the use of the BEA's chained-dollar estimates will overstate the relative contribution of these IT sector components to GDP growth.

We extend our previous work on infrastructure by deriving the returns to scale coefficient from the basic production function specification. We place no restrictions on the returns to scale, but, in fact, expect to find evidence of increasing returns to scale. We further extend the research by explicitly including IT capital as an endogenous technological growth component, and explore the hypothesis that this endogenous growth is not neutral in its impact on the marginal products of non-IT capital and labor. The statistical hunch that motivates our research is that we shall get better estimates by allowing for strategic nonlinearities in the production function. Finally, there is an active economic discussion about whether recent economic conditions support the notion of a new economy, and whether the observed gains in the growth of output per worker hour are sustainable (Oliner and Sichel, 2002; Stiroh, 2002a, b). We believe that important productivity changes have taken place and are identifiable in the parametric structure of the economy. We expect our empirical results will contribute insights to this active discussion.

1. Model

As in our previous paper, we begin with a production function that has been specified to allow for an S-shaped curve when graphing total output with respect to the labor input. In natural logarithms, we start from the following functional form:

$$\ln Q = \ln A + \alpha \ln(uK) + \beta_1 \ln L + \beta_2 \left(\frac{100}{L} - \frac{KP}{L^2} \right), \tag{1}$$

where Q is real non-residential, non-farm output, A represents the technological index, L is worker hours, K is the total stock of private real non-residential, non-farm capital, and u is capacity utilization. K can be disaggregated into the stock of private non-residential non-farm capital (KP) and government capital (KG). The KP capital stock variable can be further disaggregated into information technology capital (KIT) and other private capital (KOP). It should be noted that government infrastructure capital has been subtracted out of K.

This specification[6] is a variant of the transcendental production function classification, which is one of several functional forms used to generalize a Cobb-Douglas production function (see e.g. Intriligator et al., 1996). For our purposes, the important aspect of the function specification of Eq. (1) is that the returns to scale coefficient (RTS) is not a

[5]We wish to thank Dan Sichel for bringing this issue to our attention in his comments on an earlier draft of this paper presented at the January 2003 ASSA meetings. In addition, he pointed out the consistency between the results of this paper with those obtained by growth accounting.

[6]This equation represents a minor refinement to the one used in Duggal et al., 1999.

constant. Instead, it is a function of the capital/labor ratio which can reflect the incidence of capital deepening.

The technological index is traditionally modelled as:

$$A = \mathrm{e}^{gt}, \tag{2}$$

where g is the rate of growth of the index and t a time trend. We expand upon this approach by specifying the growth rate of the technological index to be a nonlinear function of information technology capital. Conceptually, we are putting forward the hypothesis that information technology capital has a dual role in the production process. There is the productivity impact from the traditional role of a factor input, as well as a productivity impact that works through the growth rate of the technological index. The functional form utilized needs to be flexible enough to accommodate the productivity impacts due to both the spillover effects of IT capital and the quality effect from substitution of IT capital for other types of capital. Moreover, one would not expect these productivity impacts to increase without limit. Additionally, the functional form developed should be able to identify any bias in the productivity impact of IT capital on the marginal productivities of labor and non-IT capital.

With these thoughts in mind, in order to capture all aspects of the productivity impact of IT capital, we specify the following functional form for the relationship between IT capital and the growth rate of the technological index:

$$A = \mathrm{e}^{\mathrm{e}^{[(L_{-n}kitr)^{\gamma 1} - (\gamma_2 L_{-n}/KIT)^{\gamma 3} + (Lfr)^{\gamma 4} + t^{\phi} + c]}} \tag{3}$$

where $kitr$ is calculated as $100[KIT/(\mathrm{KOP}+\mathrm{KIT})]$, fr is calculated as $100(F/KP)$, F is government infrastructure capital, t is a positive time trend used to proxy disembodied technological change, and c is a constant.

Under this specification, given appropriate values for $\gamma_{3,}$ the growth rate of the technological index with respect to IT capital will (1) increase at an increasing rate at low levels of the IT capital stock, (2) at some IT capital stock it will slow down to increase at a decreasing rate, and (3) eventually reach a plateau such that further increases in the IT capital stock will have no additional spillover effects. Increasing *kitr*, which represents a compositional change in the capital stock leading to an increase in capital quality, will have a positive impact on the technological index by shifting the curve of g graphed against KIT upward. Likewise, decreasing *kitr* will have a negative impact by shifting the curve downward due to a decrease in capital quality. Thus the functional form directly incorporates the hypothesis from the literature that capital quality, and hence the technological index, is a function of the relative composition between IT and non-IT capital (Harchaoui et al., 2002; Stiroh, 2002a, b; Jorgenson et al., 2002; Jorgenson and Stiroh, 1999).

This functional form also allows the hypothesis that IT capital is biased in its impact on the marginal product of labor relative to the marginal product of non-IT capital. The first term, $L_{-n}kitr^{\gamma 1}$, models the idea that the compositional quality impact of IT capital is enhanced at higher levels of the labor input. The second term accommodates the substitution effect between the labor input and IT capital, whereby increasing the value of the labor input in this term will decrease the magnitude of the IT capital impact on g, while also expanding the range of the increasing phase. Hence, the impact of KIT on the marginal product of labor, relative to non-IT capital, may be biased upwards, downward, or neutral depending upon the interplay of the estimated coefficient values. We acknowledge the possibility of a lagged period to this interaction effect with IT capital by including a lag on the labor input.

We complete the specification of the growth rate of the technological index by including public infrastructure capital and a time trend. However, the basic premise of this paper is that IT infrastructure works in very similar ways as public infrastructure, in that they both provide networks that increase the speed and efficiency of the production process. Therefore, given the constraint placed on the impact of IT capital to productivity by modeling it as a ratio to total private capital, consistency would imply that public infrastructure be modeled in the same manner. Consequently, unlike the model specification in our previous paper,[7] we now include public infrastructure as a ratio to total private capital. Further, considering the literature outlining the reasons why the productivity impact of IT infrastructure should be biased towards the marginal product of labor due to increased efficiency in the flow of information, there is every reason to expect that this would also be true for public infrastructure due to increased efficiencies in traveling to market locations. Once we acknowledge that both kinds of infrastructure should be modeled as a ratio to total private capital, with the expectation that both will be biased in their impact on the marginal product of labor, the question becomes whether to model them as two separate ratios, or to add the two together. We chose to model them initially as two separate ratios because of the potential for a lagged effect between labor and IT capital.

Totally differentiating Eq. (3) we obtain the following accounting for the percentage change in the technological index:

$$\begin{aligned}\%\Delta A = {} & \left[\gamma_1(L_{-n}kitr)^{\gamma_1}\left(1-\frac{KIT}{KP}\right)+\gamma_3\left(\frac{\gamma_2 L_{-n}}{KIT}\right)^{\gamma_3}-\gamma_4 Lfr^{\gamma_4}\frac{KIT}{KP}\right]\exp\ \%\Delta KIT \\ & + \left[\gamma_4(Lfr)^{\gamma_4}\exp\right]\%\Delta f \\ & - \left[\gamma_1(L_{-n}kitr)^{\gamma_1}\frac{KOP}{KP}+\gamma_4 Lfr^{\gamma_4}\frac{KOP}{KP}\right]\exp\ \%\Delta KOP+[\phi t^{\phi}\exp]\%\Delta t \\ & + \left[\gamma_1(L_{-n}kitr)^{\gamma_1}+\gamma_4 Lfr^{\gamma_4}-\gamma_3\left(\frac{\gamma_2 L_{-n}}{KIT}\right)^{\gamma_3}\right]\exp\ \%\Delta L, \end{aligned} \tag{4}$$

where $\exp = e^{[(L_{-n}kitr)^{\gamma_1}-(\gamma_2 L_{-n}/KIT)^{\gamma_3}+(Lfr)^{\gamma_4}+t^{\phi}+c]}$.

Substitution of Eq. (3) into Eq. (1) yields the structural equation to be estimated:

$$\ln Q = \alpha \ln(uK) + \beta_1 \ln L + \beta_2\left(\frac{100}{L}-\frac{KP}{L^2}\right) + e^{[(L-nkitr)^{\gamma_1}-(\gamma_2 L_{-n}/KIT)^{\gamma_3}+(Lfr)^{\gamma_4}+t^{\phi}+c]}. \tag{5}$$

The n-period returns to scale coefficient for this expanded production function is:

$$\begin{aligned}\text{RTSn-period} = {} & \alpha+\beta_1+\frac{\beta_2}{L}\left[\frac{2KP}{L}-\frac{K}{L}\frac{\Delta KP}{\Delta K}-100\right] \\ & + \gamma_1(L_{-n}kitr)^{\gamma_1}\exp\left[1+\frac{\%\Delta KIT}{\%\Delta K}-\frac{\%\Delta KP}{\%\Delta K}\right] \\ & + \gamma_3\left(\frac{\gamma_2 L_{-n}}{KIT}\right)^{\gamma_3}\exp\left[\frac{\%\Delta KIT}{\%\Delta K}-1\right]+\gamma_4 Lfr^{\gamma_4}\exp\left[2-\frac{\%\Delta KP}{\%\Delta K}\right], \end{aligned} \tag{6}$$

where $\exp = e^{[(L_{-n}kitr)^{\gamma_1}-(\gamma_2 L_{-n}/KIT)^{\gamma_3}+(Lfr)^{\gamma_4}+t^{\phi}+c]}$.

[7] See Duggal et al., 1999.

This represents the returns to scale effect over n periods from a uniform percentage increase in L, K, and F that occurred in period t-n, and then held constant through to period t. Information technology capital will always have a positive impact on the returns to scale coefficient whenever the percentage change in IT capital is greater than the percentage changes in private capital and total capital.

2. Data

The model was empirically evaluated using data for the US economy over the period 1975–2001. The lags in the first stage estimation of factor inputs required the use of pre-1975 data as well. We used the BEA National Income and Product Accounts data whenever available. The capital stock data are also from the Bureau of Economic Analysis, electronically available as part of US fixed Reproducible Tangible Wealth. Data sources other than these are identified when the variable is defined.

In contrast to our earlier paper (Duggal et al., 1999) that was started before the NIPA conceptual changes, all real quantities are now expressed in billions of chained 1996 dollars. However, we had to deal with new aggregation issues that have arisen with the chained-dollar values. In general, chained-dollar values are not additive. In particular, adding chained-dollar values of components to build our own series of capital would generate bias in cases of large price movements. Given that our goal is to study the effect of technology, the sector in which prices have declined, simple aggregation would create significant bias in our results.

We followed the BEA recommendation outlined in Landefeld et al., (2003). Accordingly, constant values were created for each variable by multiplying the previous period's current-dollar levels for the variable by the rate of increase in the chained index for the variable. The constant values for the variable thus created are additive, thus allowing construction of variables, required for the analysis, through aggregation. This method approximates the detailed level Fisher weights actually used by BEA in estimating GDP as shown in Table 4 of Landefeld et al., (2003).

2.1. The output variable, Q

The output variable used is nonfarm GDP in billions of constant dollars less the amount originating from housing.

2.2. Stock of government infrastructure, F

Government infrastructure consists of the stock of capital held by federal, state and local governments, net of depreciation, in the categories listed below:

1. Highways and streets.
2. Other buildings: includes police, fire stations, court houses, auditoriums and passenger terminals.
3. Other structures: includes electric and gas facilities, transit systems and airfields.

The BEA provides detailed capital stock data in current dollars; it also provides chain quantity indices at the same level of detail. Real stock values for each of the three components were derived using the BEA method outlined above. The values were then aggregated.

2.3. Private stock of information technology, kit

The real quantity of information technology stock was derived following the same procedure as applied to infrastructure. The capital stock was calculated as the sum of private information processing equipment, private software, and the private stock of communication capital.

2.4. The capital stock variable, K

The capital stock variable used in the production function is the sum of private non-residential and public capital, excluding military and infrastructure stock defined above.

2.5. The labor variable, L

As in the earlier paper, labor is defined as total employee hours. It is the value given in BEA Business Conditions Digest for non-agriculture worker hours.

2.6. The real user cost of capital, UCKER AND UCKSR

The user cost of equipment capital *UCKER* and of structures *UCKSR* are calculated by Global Insight Corporation of Lexington, MA, and deflated by the appropriate price indices.

2.7. The real wage rate, WR

The wage rate is calculated as the ratio of compensation of employees to hours worked. The wage rate is in real terms, i.e. adjusted for inflation.

2.8. The capacity utilization rate, u

The Federal Reserve Bulletin index was used for the capacity utilization rate.

2.9. The comparative price variable, cpv

The *cpv* variable is the product of two ratios. The first is the ratio of the GDP deflator to the nominal wage rate. The second is the ratio of the GDP deflator to the nominal user cost of equipment.

2.10. The employee benefits variable, BEN

This is obtained from Table 2.1 of the BEA National Income and Product Accounts. It is the sum of employer contributions to employee pensions, employee insurance funds, and government social insurance.

3. Estimation

Due to the lack of consistency in single equation estimation with endogenous variables, we used a two-stage least-squares procedure by first estimating the factor demands. In view of the complexity of the model, solving for the factor demand functions from the first order maximizing conditions would be even more infeasible than was the case in the earlier paper (Duggal, 1999). Consequently, the implicit function was used again to develop the specification of factor demands. The variables used in the factor demands were output, relative input prices and the price of output relative to the input prices. As before, structural behavior suggests that the input demand equations be estimated using lagged explanatory variables. The use of ordinary least squares with right-hand side lags can provide consistent estimates. Accordingly, the following input demand equations were estimated for labor and the private stock of capital[8] (t-statistics are in parentheses):

$$\underset{(11.8)}{L_t = Q_{t-1}^{.55}} \quad \underset{(-5.1)}{+\left(\tfrac{WR_{t-1}}{UCKER*cu}\right)^{-.72}} \quad \underset{(6.1)}{+(100 * CPV_{t-1})^{.47}} \quad \underset{(2.3)}{-\left(\tfrac{BEN_{t-1}}{PINDEX_{t-1}}\right)^{.44}} \quad \underset{(2.1)}{+L_{t-1}^{.71}}, \tag{7}$$

$$\bar{R}^2 = .993 \quad DW = 1.7$$

where cu is the capacity utilization rate multiplied by 100 and $PINDEX$ is the implicit price deflator, for non-residential GDP, divided by 100.

The private capital stock is built by separate estimations for equipment, KE, and structures, KS. The estimated private capital stock was added to the government capital stock, excluding government infrastructure as defined above. KIT, which is part of KE, was also isolated for separate estimation.

$$\underset{(5.0)}{KE_t = 0.22Q_{t-1}} \quad \underset{(6.6)}{+\sum_{i=1}^{11} \varphi_i \left(\tfrac{WR}{UCKER}\right)_{t-i}} \quad \underset{(4.4)}{305.6(u_{t-2} + u_{t-3})} \quad \underset{(5.3)}{+.52KE_{t-1}} \quad \underset{(-5.4)}{-733.9}, \tag{8}$$

Estimates of φ_i, $i = 1 - 11:$ 17.9, 32.5, 43.9, 52.0, 56.9, 58.5, 56.9, 52.0, 43.9, 32.5, 17.9

$$\bar{R}^2 = 0.999, \quad DW = 1.7,$$

$$\underset{(6.1)}{KIT_t = 0.76KIT_{t-1}} \quad \underset{(-4.1)}{+\sum_{i=1}^{11} \Omega_i UCKER_{t-i}} \quad \underset{(2.7)}{+0.03\sum_{i=2}^{4} Q_{t-i}} \quad \underset{(5.5)}{+37.4}, \tag{9}$$

Estimates of Ω_i, $i = 1 - 11:$ −0.31, −0.56, −0.76, −0.90, −0.98, − 1.01, −.98, −.90, −0.76, −0.56, −0.31

[8]We treat public infrastructure as capital formation that is exogenous, hence an input demand function is not estimated for F. See Duggal et al., 1999.

$$\overline{R}^2 = 0.999, \quad \mathrm{DW} = 1.6,$$

$$\underset{(24.2)}{KS_t = .84KS_{t-1}} + \underset{(5.7)}{\sum_{i=1}^{11} \Phi_i \left(\tfrac{P}{UCKSR}\right)_{t-1}} \underset{(6.5)}{+6.1(L_{t-1} + L_{t-2})} \underset{(-7.8)}{-2232.8}, \tag{10}$$

where P is the implicit price deflator for -nonresidential GDP.

Estimates of $\Phi_i = 1 - 11$: 27.3, 49.7, 67.1, 79.5, 87.0, 89.4, 87.0, 79.5, 67.1, 49.7, 27.3

$$\bar{R}^2 = 0.999, \quad \mathrm{DW} = 1.97.$$

Utilizing the input factor demand equations, the estimated values of labor, total capital and information capital were calculated and substituted into the structural equation specified by Eq. (5). This equation was then estimated using a variant of the Levenberg–Marquardt nonlinear estimation technique.

There were several unforeseen aspects to the initial estimation results. The coefficient on the $L_{-n}kitr$ variable was not significant unless both L and *kitr* were lagged to the same time period, indicating that the ratio as a whole has a lagged effect with labor. The coefficient became significant at both a 3- and 4-period lag for all components of the variable (*L*, *KIT*, and *KOP*). The *t*-statistics were the highest, for all variables in the equation, and the standard error of the regression the lowest when using a 4-period lag. Also, when using a 4-period lag, we could not reject the null hypothesis of zero autocorrelation in the residuals; the probability of not rejecting ranging from 40% to 80%. However, the probability of not rejecting the null hypothesis with respect to the residuals ranged from 70% to 100% when using a 3-period lag. Consequently, it was decided to use the sum of the third and fourth period lagged values for all components of the variable. This resulted in a lower standard error than that from either of the equations with just a 3- or 4-period individual lag. With regard to the infrastructure variable, *Lfr*, it was a surprise to find that it also did not become statistically significant until all components were lagged to the same time period. Again the coefficient was significant at both a 3-period and 4-period lag so, as before, the decision was made to use the sums.

Estimation of the equation with the sums of the 3- and 4-period lagged *kitr* and *fr* ratios resulted in estimated values of $\gamma_1 = 0.094$ and $\gamma_4 = 0.10$. The Wald test of the null hypothesis that $\gamma_1 = \gamma_4$ produced a chi-square statistic of 0.017, meaning that the null hypothesis could not be rejected with a 90% probability. Hence, it was decided to estimate the equation with the sums of the 3- and 4-period lagged ratios added together. The results are presented below:

$$\ln Q = .67 \ln(u\hat{K}) + .33 \ln \hat{L} + .96 \left[\frac{100}{\hat{L}} - \frac{\hat{K}P}{\hat{L}^2} \right] \times \mathrm{e}^{\left[\left(100\left(\frac{Sm\hat{L}*(SmK\hat{I}T+SmF)}{Sm\hat{K}P}\right)\right)^{.12} - \left(\frac{1.67\hat{L}_{-1}}{K\hat{I}T_{-1}}\right)^{3.04} + t^{.27} - 5.92 \right]} \tag{11}$$

(5.0) (1.9) (2.5) (2.0) (8.8) (3.9) (4.9) (−3.3)

$$\overline{R}^2 = 0.999, \quad \mathrm{DW} = 2.18,$$

Table 1
Integrated conditional moment test

$w(\cdot) = \cos(\cdot) + \sin(\cdot)$			
Monte Carlo simulations	Lag$\geqslant$1	Lag$\geqslant$6	Lag$\geqslant$11
5000	2.05	1.77	1.88
10,000	2.07	1.78	1.99
$w(\cdot) = \exp(\cdot)$			
Monte Carlo simulations	Lag$\geqslant$1	Lag$\geqslant$6	Lag$\geqslant$11
5000	2.29	1.01	1.06
10,000	3.00	0.85	0.63

Critical values of the ICM statistic are: 3.23 for 10% and 4.26 for 5%.

where $SmL = (L_{-3} + L_{-4})$, $SmKIT = (KIT_{-3} + KIT_{-4})$, $SmKP = (KIT_{-3} + KIT_{-4} + KOP_{-3} + KOP_{-4})$ and $SmF = (F_{-3} + F_{-4})$. Ljung–Box Q-statistics for $k = 4$ and 12 are 2.190 and 10.242, respectively. The standard errors used to derive the reported t-statistics for the production function are calculated by replacing the first stage factor input values by the corresponding actual values.

We undertook Bieren's integrated conditional moment test of functional form to validate the specification of the nonlinear structural equation. The test was done in a manner identical to that in the previous paper. The interval of the two-dimensional maximization was set as before:

$$[-5, \quad 5] \times [-5, \quad 5].$$

The lags of the explanatory variables were set at greater than or equal to 1, greater than or equal to 6 (the average weighted lag of the relative price variables in the estimated factor demand functions), and greater than or equal to 11 (the maximum lag in the estimated equations). We performed 5,000 and 10,000 replications using, alternatively, the trigonometric and the exponential weight functions. The ICM statistic in all 12 simulations presented in Table 1 is considerably less than the critical values. The null hypothesis of independence between the explanatory variables and the residual error term cannot be rejected even at the 10% significance level. The strong evidence of independence supports the hypothesis that the production function is not mis-specified.

4. Productivity analysis

4.1. The marginal product of labor

The marginal product of labor is evaluated for the economic conditions of 1990 and 2001. These graphs are, as before, classic textbook cases with marginal product rising at low levels of labor input, reaching a maximum and then declining. At advanced activity levels of the economy, with the correspondingly larger capital stock, the maximum marginal product of labor is reached at a higher labor value. The marginal product at the 2001 level of 239.7 billion man hours is 25.0 billion constant dollars. The same level of labor when combined with 1990 capital stock would have yielded a value of $4.7 billion for the marginal product of labor. The marginal product of labor turns negative with 1990 values of capital stock when labor becomes redundant at 310 billion man hours (Fig. 1).

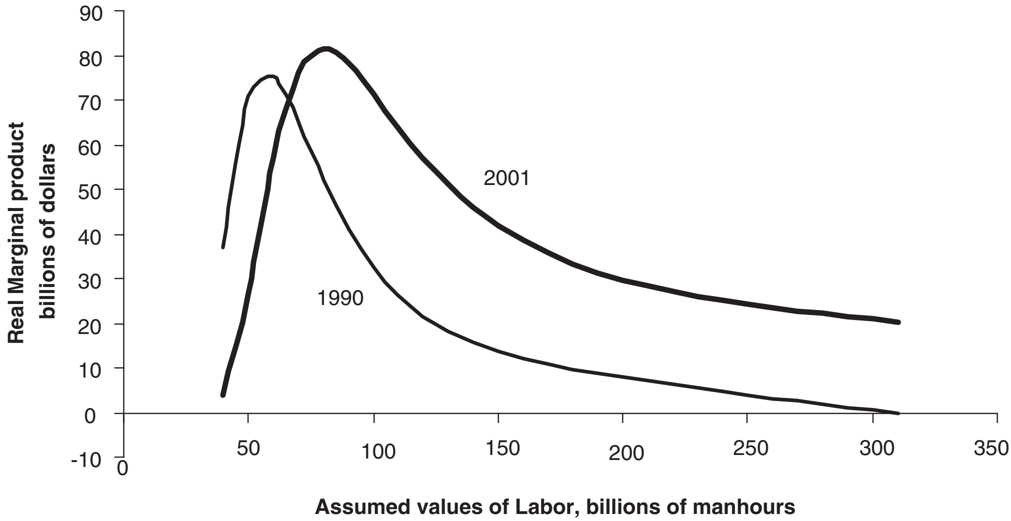

Fig. 1. Marginal product of labor evaluated at conditions of 1990 and of 2001.

4.2. *Marginal product of all capital*

We calculate the marginal product of capital by increasing all capital assuming fixed ratios of technology, equipment, structures and government capital to overall capital at 2001 and 1990 levels as the case may be. The two curves presented in Fig. 2 are S-shaped curves rising at low level of capital, reaching maximums and then declining. At 2001 level of capital of $14 trillion, the marginal product is 200 million constant dollars.

4.3. *Marginal product of technology capital*

The marginal product of technology capital is presented in Fig. 3 using 2001 and 1990 economic conditions. Higher conditions specifically represented by higher labor and higher overall capital generates higher marginal products at low levels of technology capital. This pattern holds as the marginal product slides downwards rapidly with increases in the technology capital. The rate of decrease of the marginal product declines continuously with increases in technology capital, and the value of the marginal product becomes asymptotic to the x-axis. The long run marginal product is 1 billion constant dollars at the 2001 value of technology capital and labor, five times higher than the marginal product of overall capital at current levels.

4.4. *Effect of IT capital on the technological index*

As has been stated, the IT capital plays a dual role in the production process. The first role is the standard role of a factor input. The second and the more interesting role is the contribution of IT capital on the technological index. Graphs of two simulations are presented in Fig. 4 to isolate this effect using the 1990 and 2001 conditions of the economy when IT capital is increased over the range of values up to $2 trillion. The value of the

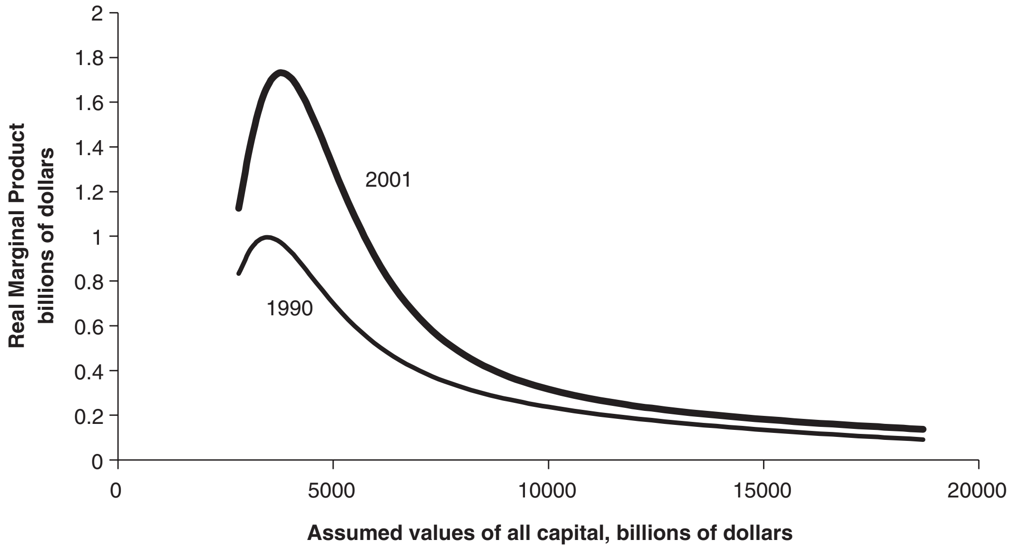

Fig. 2. Marginal product of all capital evaluated at conditions of 1990 and of 2001.

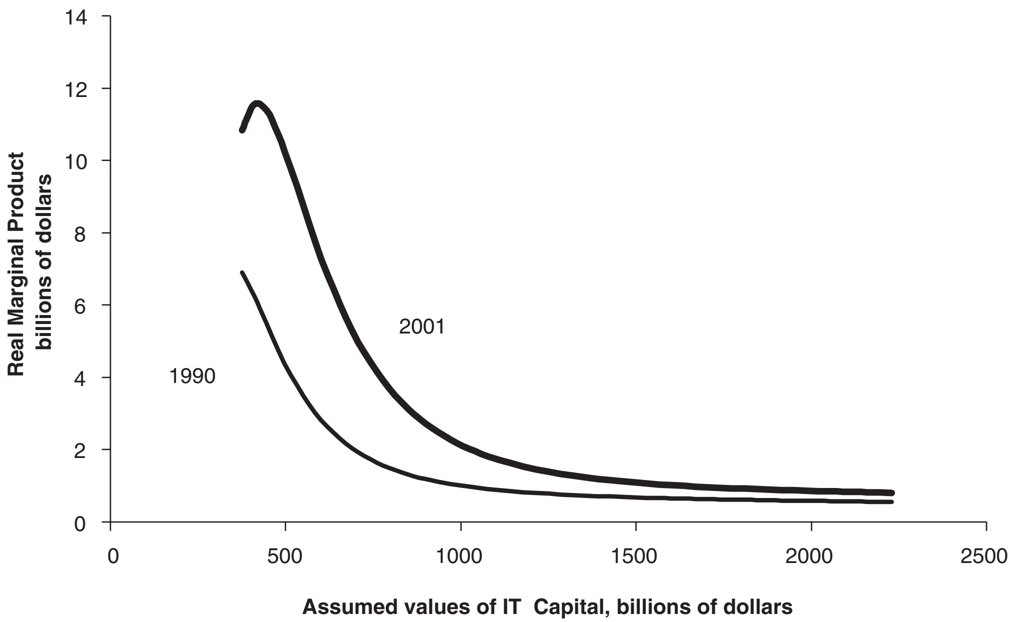

Fig. 3. Marginal product of technology capital evaluated at conditions of 1990 and of 2001.

Y-axis is the multiplicand to the combined contribution of factor inputs K and L resulting in total output. This multiplicand is close to one up to an IT capital level of \$250 billion at both conditions. With increases in IT capital, the multiplicand increases rapidly reaching 2 at \$700 billion with 2001 economic conditions and at \$1.75 trillion with the 1990 scenario. The rate of increase slows down and the effect plateaus with further increases in IT capital.

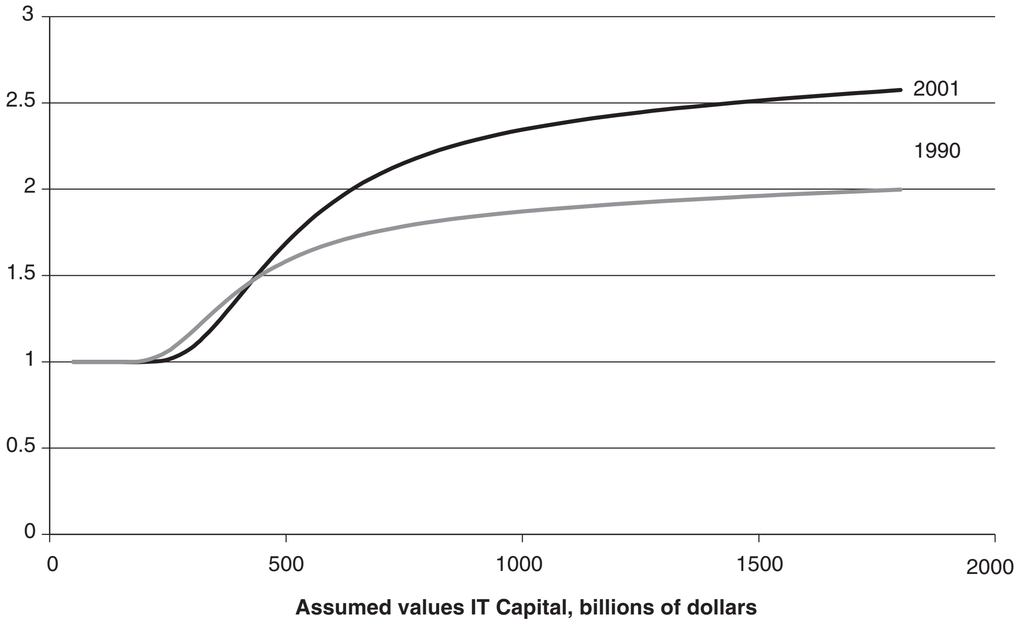

Fig. 4. Effect of IT capital on the tech index evaluated at conditions of 1990 and 2001.

The contribution of IT capital on the technological index for the 2001 level of IT capital of \$1.628 trillion is a little over 2.5 as measured by the structural equation.

4.5. Factor productivity

The components of the growth accounting calculation are presented in Table 2, beginning in 1993 through to the end of our data set in 2001.

It is clear to see from the table that information technology capital has been a consistent and significant contributor to economic growth during the expansion of the 1990s, following a steady upward trend during the time period. Government infrastructure has also been a reliable source of growth, which appears to have jumped to a higher trend line in 1998. One of the most interesting aspects of the table is the growth attributed to labor which implies a dramatic increase in labor productivity occurring between 1996 and 1997.

4.6. Returns to scale

The formula for calculating returns to scale is presented in Eq. (6), above. This is given for an estimation of the returns realized over n periods. We analyzed returns to scale from the estimated Eq. (11) for the increase in output achieved after four periods resulting from a one time equal increase in L, K, and F. The results, shown in Table 3, indicate that output would gradually rise by a factor of 1.191 over four-year periods starting in 1993 and ending in 2001. This is evidence for a significant presence of increasing returns to scale in our dynamic production process.

Table 2
Factor growth accounting

$\%\Delta Q$	1993	1994	1995	1996	1997	1998	1999	2000	2001
	5.73	7.17	5.88	5.20	7.24	5.60	5.60	5.56	1.37
Due to a%Δ in:									
KO	.37	1.05	.87	1.53	.88	.82	.44	.84	.65
KIT	1.06	1.11	1.17	1.21	1.32	1.39	1.32	1.44	1.29
L	.77	.36	.08	.71	1.43	1.32	1.12	1.32	.84
F	.77	.95	.74	.59	.77	1.11	1.38	1.31	1.26
u	.81	1.75	.09	−.78	.84	−1.01	−.68	.07	−4.69
t	1.95	1.95	1.93	1.95	1.99	1.97	1.99	2.07	2.01

Note: Columns may not add up due to rounding.

Table 3
Returns to scale evaluated over the period 1994–2001

Year	1993	1994	1995	1996	1997	1998	1999	2000	2001
	.969	1.051	1.059	1.086	1.059	1.089	1.139	1.165	1.191

For general background information in support of our hypothesis that increasing returns were present for the US economy during the unusual growth period of the 1990s, in which decade-long expansion took place without inflationary pressure, the gains in productivity that allowed this development to take place probably arose, in part, from increasing returns to scale captured by the industrial economies. In general discussions of this subject, it has been noted that there was an extraordinary rise in the occurrence of mergers and acquisitions in the United States. Eventually this occurred as well in cross-border mergers and acquisitions. The process was quite noticeable all during the 1990s, but accelerated markedly after 1995, and much of this business activity occurred in connection with information technology. These mergers were often rationalized in public, as being stimulated by the opportunity of realizing the gains of scale (in production, marketing, office operations, and financing). This motivates our choice of specification that permits nonconstant returns to scale, and is supported by our parameter estimates that such a motivation is justified.

4.7. Out-of-sample forecast

Out-of-sample data were used to generate a post sample forecast. The first ex-post calculation is generated by estimating factor demands for 2002 and 2003 using actual relative prices and output, the explanatory variables in the first stage of the structural estimation of the production function. After adjusting for the most recent errors of the factor demand equations, the predicted values were inserted in the estimated production function. The implied growth rates for real GDP are presented in Table 4[9] as are the actual growth rates. As can be seen, the growth rates implied by the full structural system of

[9]The values of GDP for 2002 and 2003 are extended beyond 2001 by the same method that was used for the sample values.

Table 4
Growth rate of real GDP—ex-post forecast

Year	Actual	Forecast
2002	3.956	3.910
2003	5.092	5.054

equations closely parallel the actual rates. The predicted growth rate differs from the actual by less than .05 percentage points in both years. The disparities in the growth rates are remarkably small, 1.16% and .75% in 2002 and 2003, respectively.

5. Conclusions

Motivating factors behind our focus on IT capital, within a macroeconomic framework, are to explore the conditions under which the dynamics of productivity, or technical efficiency, underlie the operation of the US economy. The underlying statistical data for information technology inputs, their use in the production process, with variation over time and across sectors of the economy, are basic to an understanding of the revival of productivity in the United States during the 1990s.

Most empirical studies in this area make restrictive assumptions that enable some measures to fall into place with ease. In particular, the restriction, often imposed for mathematical tractability, of constant returns to scale is unjustified when studying the dynamics of technical change. In this study, we have shown that it is feasible to describe and estimate, from realistic macroeconomic data, production curves that exhibit the properties of an S-shape functional form, the traditional shape that rarely gets empirically estimated. Estimating an *S*-shaped functional form is important because it allows relatively undeveloped economies (or industries) to expand quickly at high marginal rates if the appropriate economic policies or technical events are put into place.

We have followed the arguments and presentations in Intriligator, et al. (1996) in which capital deepening is expressed by key ratios between pairs of factor inputs that are used. This provides a very general way of accomplishing two things by an extended specification: (1) an S-shape (in two-dimensional cuts); and (2) fast enough growth to permit increasing returns to scale. It is not natural or fruitful to look for significant technical developments of the 1990s under the simplifying assumptions of decreasing or constant returns to scale. The functions that we have estimated allow for decreasing, constant, or increasing returns to scale, thus permitting the data of the economy to identify the phase in which US policy makers find themselves.

At the beginning of the productivity surge, under the leadership of the IT sector, the US economy experienced significant infrastructure development. The deregulation of the broad communications sector laid open the entry of private companies, and more lightly regulated sectors of the economy could add a great deal of private infrastructure needed for IT expansion. Private communications companies recognized the gains that could be made through exploitation of the presence of increasing returns. This study quantifies the macroeconomic gains realized from these increasing returns to scale. Our findings indicate that both IT capital and public infrastructure make significant contributions to technological progress, and together constitute the predominant share in growth accounting from our estimated production function.

Moreover, the estimated lag structure for infrastructure's impact on the technological index has important implications concerning expectations about labor productivity. In Table 2, the spike upward in labor productivity between 1996 and 1997 is something to look for in the early part of this 21st century. Likewise, the relative slow down in the growth rate of IT capital that occurred after the year 2000 should be reflected by a decline in the growth rate of labor productivity in 2004 and 2005; and the recent increase in the growth rate of IT capital should generate increases in labor productivity growth four years hence.

At this point in time, it is clear to us, that the global expansion of IT infrastructure will have important impacts on country specific rates of macroeconomic growth. This has particular relevance to ''off-shoring'', the lively topic of the moment, where we find that large purveyors of software deem it useful to invest in overseas infrastructure in order to make ''off-shoring'' work well. Our positive findings in the present study indicate that ''off-shoring'' infrastructure and more detailed specification of human capital input will be significant in finding when productivity will probably expand again at a high rate.

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