

Is there an ICT impact on TFP?:  
Evidence from industry panel data<sup>\*</sup>.

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Abstract

This paper uses a new set of industry data for the US and the UK non-agricultural market economy, to provide new evidence on the impact of ICT on TFP. We compare the results from standard panel data techniques with newly developed dynamic panel data estimation methods. The traditional industry panel data analysis fails to find a significant impact of ICT on output/TFP growth. This paper argues that this is due to heterogeneity across industries, particularly in the time dimension. An alternative technique which allows the dynamic specification to vary across industries yields a positive and significant long-run impact of ICT on TFP.

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## 1. Introduction

The debate on the impact of the ‘New Economy’ on output and productivity growth has exercised the minds of many economists in the past decade. It has now become commonplace to divide the growth in labour productivity into contributions from additional capital per worker (capital deepening) and underlying total factor productivity (TFP) growth. Following a rigorous debate there is little doubt now that investment in Information and Communications Technology (ICT) equipment has had a significant impact on US labour productivity growth in the 1990s through the capital deepening channel and evidence is also emerging of high contributions from ICT capital in European and other OECD countries<sup>1</sup>. There is much less consensus on the question of whether changes in information technology have had an impact on the underlying rate of technical progress or TFP. Gordon (2000) suggested that the TFP acceleration in the US in the late 1990s was entirely concentrated in the ICT producing sectors. On the other hand, the Council of Economic Advisers (2001), argued that the US TFP acceleration in the latter half of the 1990s is also pronounced in industries which are among the most intensive users of ICT equipment. Subsequent research appears in general to support this position (Van Ark 2001, Basu et al. 2001).

Much of the evidence on the impact of ICT capital deepening is derived from the growth accounting index number method which weights growth in inputs by their share in the value of output. When searching for a direct effect of ICT on TFP, however, an econometric approach is needed. TFP growth stemming from investment occurs through a divergence between private and social returns usually described in

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<sup>1</sup> See e.g. Jorgenson and Stiroh, 2000, Oliner and Sichel, 2000, 2002, for US evidence, Colecchia and Schreyer, 2001, for OECD countries both Oulton, 2002, and Cetto et al. 2002, for single country studies.

terms of network spillovers. Since the market does not remunerate returns from spillovers, these potential productivity enhancing activities cannot be incorporated in an index number approach and hence require estimation.

This paper presents evidence on the impact of ICT on output growth and TFP, using a unique industry data set covering the entire non-agricultural market economy in the US and the UK. Arguably the most attractive approach to estimating spillover effects or those arising from organisational changes is to employ firm level data which control for influences other than ICT on TFP growth. Many such studies do suggest that innovations in information technology have an important impact on TFP growth (Brynjolfsson and Hitt, 1996, Black and Lynch, 2000). However, these micro studies are often confined to particular samples, e.g. large firms and/or particular sectors such as manufacturing, and so do not yield an estimate of an aggregate economy wide impact of ICT on TFP. The latter requires an analysis which covers all sectors within this aggregate; industry level data represents a valuable option. However analyses using panel regression on industry data generally show small or negative returns from ICT investment (Stiroh, 2002b).

This paper extends the existing evidence by focusing on two issues that are likely to play an important part in the investigation of the ICT impact on output growth and TFP, namely, industry heterogeneity and stationarity of the data. Firstly our data set, which includes both manufacturing and non-manufacturing industries, show wide variation in the pattern of ICT investments. For example, in communications around 80% of the total capital stock is ICT capital, while this ratio is under 10% in many traditional manufacturing industries such as textiles. Hence a methodology that can adequately account for this heterogeneity is important. Secondly, with 24 years of observations for each cross section, the dynamic pattern of

the data cannot be neglected. Therefore the main body of the empirical analysis will employ a methodology that accounts for heterogeneous dynamic panels (Pesaran et al., 1999).

The next section sets out the theoretical framework which underlines much of the research on this topic. Section 3 briefly describes the industry panels employed in the two countries and sketches the measurement issues underlying the construction of these data. Section 4 begins with a presentation of results using a traditional panel regression approach, employed in the literature up to now, to show that the generally negative findings on ICT capital hold for the data employed in this paper. We then consider reasons why the standard approach may be an inadequate representation of the dynamic adjustment process of technology diffusion and we present an alternative analytical framework (sections 5 and 6). Finally we present estimates based on the pooled mean group (PMG) estimator outlined in Pesaran et al. (1999). This approach yields estimates which are at variance with the simple panel regression model and suggests a positive and significant ICT impact on output and TFP growth. Section 8 concludes the paper.

## **2. Modeling the impact of ICT on TFP: The ‘special capital’ model.**

The most common approach to modelling the impact of ICT on TFP has been termed the ‘special capital’ model (Schreyer 2000). This treats a particular input (in this case ICT capital) as yielding network externalities or spillovers, which imply a social rate of return significantly above the private market rate.

The starting point for this analysis is a production function of the form:

$$(1) \quad Q_{it} = A_{it} F(K_{it}, L_{it})$$

where  $Q$  is real output,  $L$  is labour input (hours worked),  $K$  is capital input,  $A$  is a technology shift parameter and  $i$  and  $t$  denote industries and time respectively.

Suppose total capital input is a weighted average of two types, ICT (I) and non-ICT (N). Letting lower case letters denote logs, and assuming constant returns to scale, the growth in output can be decomposed into contributions of factor inputs and TFP using the Tornqvist discrete approximation to the Divisia index (Joergenson et al. 1987) given by:

$$(2) \quad \Delta q_{it} = \Delta tfp_{it} + s_{li(t,t-1)} \Delta l_{it} + (1 - s_{li(t,t-1)}) (s_{i(t,t-1)}^N \Delta k_{it}^N + s_{i(t,t-1)}^I \Delta k_{it}^I)$$

where  $s_l$  is the share of labour in value added,  $(s^N + s^I = 1)$  are the shares of I and N in the total value of capital (with all shares averaged over periods  $t$  and  $t-1$ ).

Alternatively we can start by specifying a functional form for the production function, e.g. the Cobb Douglas, given by:

$$(3) \quad Q_{it} = A_{it} L_{it}^{\alpha_1} K_{it}^{\alpha_2}$$

Assuming that the total capital stock is the sum of ICT and non-ICT capital, taking logs and first differences we can rewrite (3) in a form amenable to econometric estimation as:

$$(4) \quad \Delta q_{it} = \alpha_{0i} + \alpha_{1i} \Delta l_{it} + \beta_{2i} \Delta k_{it}^N + \beta_{3i} \Delta k_{it}^I + \varepsilon_{it}$$

Retaining the assumption of constant private returns, suppose that there are external or social increasing returns to ICT capital. Equation (4) can, in theory, be used to test for increasing returns associated with ICT capital by comparing the regression result with the sample average growth accounting coefficient on ICT capital given for each industry and time period by:  $(1 - s_{li(t,t-1)}) s_i^I(t, t-1)$ . If the estimated coefficients were found to be significantly greater than the latter expression then this might be evidence for increasing external returns from ICT capital. If this

difference is not related to unmeasured inputs then it suggests an impact of ICT on underlying productivity growth or TFP.

The existing literature has put forward several reasons to explain the divergence between the estimated returns to ICT and the growth accounting coefficient. These include errors in the measurement of output, increasing returns to scale and imperfect competition. It may also reflect underestimation of input growth, due to for example to changes in labour quality, that may be correlated to ICT capital (Stiroh 2002a, 2002b), and the impact of investments in organisational change (Black and Lynch, 2001). In principle industry data on labour force skills could be incorporated into the analysis, as could increases in organisational inputs such as consultancy fees. However data on these inputs are not easily available at the level of the industry detail used in this paper. Hence a positive impact of ICT on TFP needs to be interpreted with care and can be seen only as suggestive of the presence of spillovers.

### **3. Data and measurement issues.**

The results in this paper are based on industry panel data, comprising annual series from 1976 to 2000 for 55 separate sectors, 31 in the US and 24 in the UK covering the non-agricultural market economy<sup>2</sup>. Thus it excludes sectors within the public domain in at least one country where output measurement presents severe difficulties. The list

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<sup>2</sup> **US Industry List:** see footnote to Figure 1 below. **UK Industry List:** as for the US except that the following industries are combined: basic metals with fabricated metal products; electrical, electronic and communications equipment with office machinery and instruments; motor vehicles with other transport equipment; and motor vehicles sales & repair with wholesale trade. In addition all transport sectors are combined into a single group (24 industries).

of sectors was dictated largely by the availability of investment series required to estimate ICT and non-ICT capital stocks.

Output is real value added rather than the theoretically preferable gross output measure (Stiroh, 2002) due to the lack of reliable data for the UK in industries outside manufacturing. Labour input is annual hours worked. Capital input is measured using Tornqvist capital services indices comprising three assets categories within ICT capital (computers, software and communications equipment) and three within non-ICT capital (structures, non-ICT equipment and vehicles). Capital stocks were estimated for each asset using the perpetual inventory method, assuming exponential depreciation with rates which vary across industries but are assumed common in the same industry in the two countries. Indexes of capital services were then derived by weighting the growth rate of each asset type by its share in the nominal value of total capital services employing user costs rather than asset acquisition prices. US deflators, in particular the computer hedonic price index, adjusted for exchange rate movements, were employed for the UK and were based on those reported in Oulton (2002). All data series are based on National Accounts figures; for additional details see O'Mahony and deBoer (2002) and O'Mahony and Timmer (2002).

Table 1 summarises some aspects of the data for the entire pooled sample and each country individually. Overall in our sample output grew at just over two per cent per annum, of which just over half was due to TFP growth. Labour input declined on average in the pooled sample with a positive value in the US sample more than offset by the negative entry for the UK. The average annual growth rate of ICT capital was very large in both countries but its value added share was very low. Hence multiplying the growth rate of ICT capital in Table 1 by its share suggests about 20% of output growth in our sample was due to investment in ICT capital. The percentage

point contribution for the US was greater than the UK, with the higher ICT share for the US outweighing the lower average growth rate.

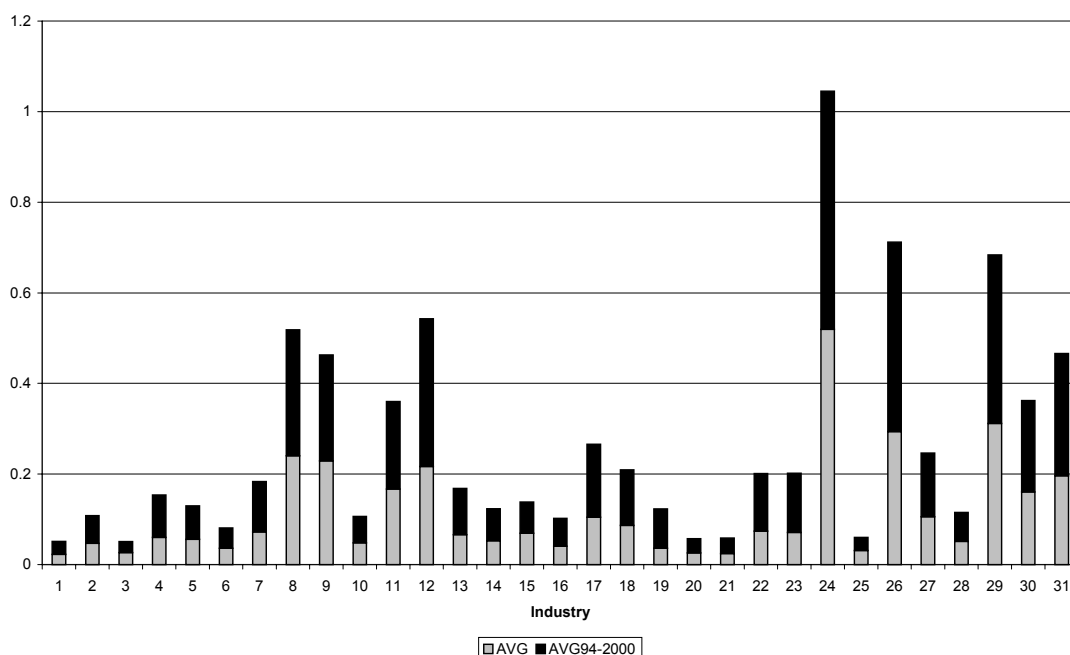
**Table 1. Data Summary, annual average per cent, 1977-2000.**

	Output	Labour	ICT capital	Non-ICTcapital	TFP
A. Pooled sample					
Growth rate	2.28	-0.06	17.61	2.05	1.22
Output shares	-	69.48	2.92	27.6	-
B. US					
Growth rate	2.87	0.88	15.31	2.21	1.17
Output shares	-	70.42	3.48	16.10	-
C. UK					
Growth rate	1.51	-1.29	20.55	1.85	1.29
Output shares	-	68.25	2.19	29.55	-

Figure 1 shows the average ICT to total capital ratio (ICT/TK) by industry for the US, computed over the entire sample and the sub-sample 1994; similar patterns can be observed in the UK. This illustrates the cross-industries differences in the importance of ICT investments relative to other forms of capital. All industries have experienced an increase in the ICT/TK in the 1990s, with Office equipment, Electrical Engineering and Instrument Engineering being characterised by the highest ratio within manufacturing. In non-manufacturing has the highest ratio, mainly due to high investments in communications equipment, followed by wholesale trade and financial services.



**Fig. 1: ICT/Total capital ratio in the US**



1=mining, 2=electricity, gas and water, 3=coal and petroleum products, 4=chemicals, 5=rubber and plastics, 6=basic metals, 7=metal products, 8=office and mechanical engineering, 9= electrical engineering, 10=motor vehicles, 11=other transport equipment, 12=instrument engineering, 13=textiles, clothing and leather, 14= food drinks and tobacco, 15= Non-metallic mineral products, 16= wood products, 17=paper and printing, 18= miscellaneous manufacturing, 19=construction, 20= railways, 21=water transport, 22=air transport, 23=transport and transport services, 24= communications, 25=motor vehicles sales and repair, 26= wholesale trade, 27= retail trade, 28= hotels and catering, 29= financial intermediations, 30= business services, 31= miscellaneous personal services

#### 4. Econometric Results: the basic model

In this section we present the results based on standard panel data estimation to check if results found in the literature to date also hold for the industry panel employed in this paper. Results are presented for both a fixed effect specification in levels, where industry specific dummies are included in the equation in levels, and a specification in first differences<sup>3</sup>. The data has been pooled across the two countries, while the introduction of interactive dummies allows for different coefficient estimates in the US and the UK. Time dummies have been added to all specifications. Although

<sup>3</sup> All variables were indexed to equal 100 in the initial year, 1976.

similar specifications are used in much of the literature, studies vary according to whether they take account of industry heterogeneity by including industry fixed effects and/or time dummies which are highly correlated with ICT capital (Stiroh, 2002b). We take the view in this paper that results are unconvincing if they do not take account of both aspects of the data.

Table 2 presents the results from the estimation of equation (4), the production function. The first two columns report the results derived from the specification in levels. For the total pooled sample and each country individually the coefficient on labour input is considerably smaller than that implied by a growth accounting calculation (see table 1) while the non-ICT capital coefficients are more plausible in this respect. However the results show a significant negative coefficient on ICT capital. The first difference specification (Table 2, column 3 and 4) shows somewhat more plausible coefficients on non-ICT inputs, at least for the US, but the coefficient on ICT capital remains negative, although not significantly so.

Recall that in this production function specification the coefficient on ICT measures the sum of the internal benefits to firms in the industry and any external spillover effects. Taken literally these results imply either that the market return on ICT capital is negative or this is positive but negative external effects outweigh any positive private benefits from investing in this type of capital. Similar results for US manufacturing results were found by Stiroh (2002a).

Many researchers working with these industry data are somewhat puzzled by these negative results on ICT capital. First the finding that the sum of private and social returns to ICT capital is negative is hardly consistent with recent models of growth resulting from general purpose technologies (GPT) such as ICT (Helpman 1998). Also a casual examination of the industry data suggests that both labour

productivity and TFP growth have been higher in industries where ICT is used intensively. There is a large and growing literature suggesting that productivity gains in the US, and possibly also in Europe, tend to have been large in industries that are intensive users of ICT (O'Mahony and deBoer 2002, van Ark 2001 and van Ark et al. 2002).

To explore these results further we experimented with a number of alternative specifications, for example including the growth of total capital and the ICT capital share as regressors to assess the relationship between the intensity of use of ICT and the rate of growth of TFP. This yielded a positive and significant coefficient on ICT shares confirming the findings from the above literature. We also looked at the industry by industry results and these showed a very wide variation in the estimated coefficients on ICT capital depending on the specification. For example, regressing current period output on current inputs industry by industry yields positive and significant coefficients in only a minority of our 55 industries. Instrumental variable techniques were also employed, with lagged values of explanatory variables used as instruments but these did not lead to significant changes in the results. Perhaps the most successful of these simple specifications is the one where the acceleration in TFP growth was regressed on the growth of ICT, which yielded high positive and significant coefficients in the majority of industries. These results suggest that there is no simple specification that is valid for all industries, and in particular that industries are likely to be subject to different dynamic adjustment processes. This in turns suggests that we should specifically account for heterogeneity using a more suitable technique.<sup>4</sup>

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<sup>4</sup> Results are available from the authors on request.

**Table 2*****Panel Regressions, Production Function estimation, 1977-2000.*****(No. Observations = 1320)**

	Levels		First Difference	
	Dependent variable: $q_{it}$		Dependent variable: $\Delta q_{it}$	
<i>Pooled coefficients</i>				
Labour	0.333*	-	0.468*	-
	(12.4)		(6.61)	
ICT Capital Services	-0.048*	-	-0.026	-
	(4.90)		(1.51)	
Non-ICT Capital services	0.362*	-	0.233*	-
	(11.0)		(4.23)	
<i>US Coefficients</i>				
Labour	-	0.382*	-	0.648 *
		(6.48)		(6.03)
ICT Capital Services	-	-0.078*	-	-0.031
		(5.92)		(1.39)
Non-ICT Capital services	-	0.141*	-	0.187*
		(6.19)		(2.17)
<i>UK coefficients</i>				
Labour	-	0.348*	-	0.290*
		(10.6)		(3.59)
ICT Capital Services	-	-0.047*	-	-0.019
		(4.96)		(0.86)
Non-ICT Capital services	-	0.311*	-	0.285*
		(8.72)		(4.16)
Adjusted R <sup>2</sup>	0.869	0.866	0.283	0.295

Notes: Absolute values of t-ratios in parentheses, standard errors are heteroscedastic consistent, \*significant at 95% level, no. industries = 55, time dummy variables are included in all equations with industry fixed effects included in the levels equations and a UK intercept dummy in the first difference specification.

## **5. Industry heterogeneity and the time series patterns of output and inputs.**

There are aspects of the existing literature to date on the impact of ICT on output growth and TFP that have not been adequately addressed. These relate to the heterogeneity of the data. As illustrated in figure 1, there are large differences in the importance of ICT investments by industry and these differences are unlikely to be adequately captured by the mere inclusion of time invariant industry dummies.

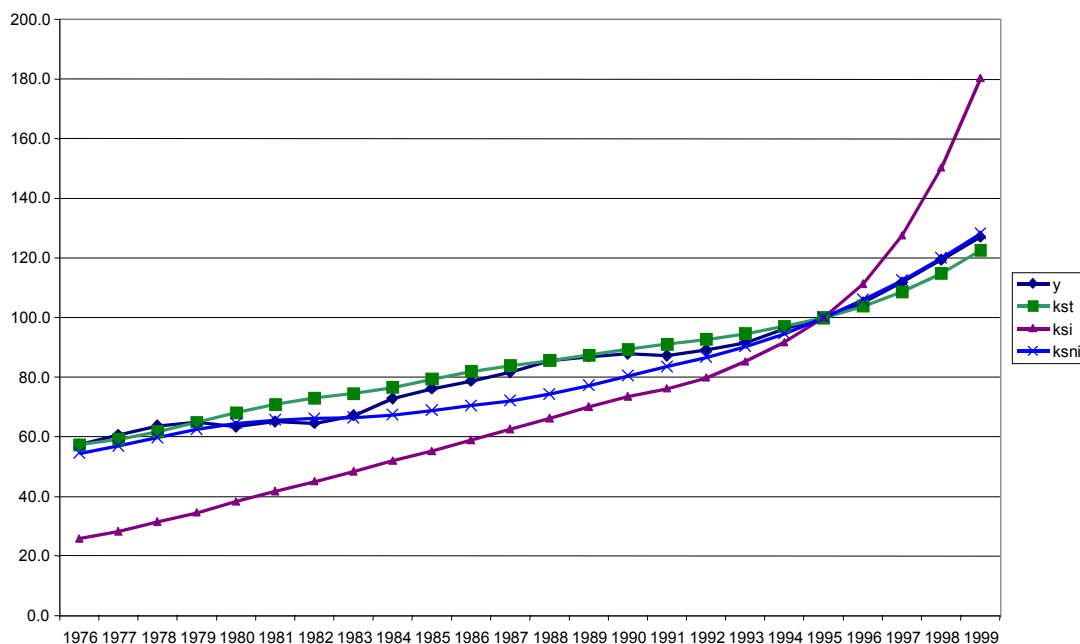
Related to this is the time series pattern of the data. Figure 2 plots output against ICT capital, non-ICT capital and total capital services using the average levels across the 31 US industries (a similar pattern emerges for the UK). This shows that all variables exhibit a clear upward trend, which is particularly strong in the case of the ICT capital. This reflects the very fast growth in ICT investments in the 1990s.

The simple OLS model used in the previous section is based on the assumption of stationarity of all the variables included in the regression and homogeneity of the coefficients across all industries and no allowance has been made for short-run dynamic effects. If these assumptions are not met we might be dealing with highly misleading results. Both of these issues have been largely overlooked in the literature on the impact of ICT capital on productivity. However, in the type of industry data employed in this paper, with 55 industries and 24 years of observation for each industry, we introduce a substantial time dimension and heterogeneity in the analysis.

When the time dimension increases, not only does the assumption of dynamic homogeneity becomes less plausible (Im et al. 2002) but also the traditional estimation procedures for pooled models, like the fixed effect or the GMM estimator, can produce highly inconsistent results (Pesaran and Smith 1995). While first differencing can sometimes address the time series side of the problem, it also drops

all information regarding the industry specific effects that can be very important in evaluating the impact of ICT on productivity. Therefore, this second part of the paper will apply a relatively new estimation technique developed by Pesaran et al. (1999) which specifically accounts for heterogeneity and the time series properties of the data. This investigates whether, by using a technique more suitable to the structure of our data, we can reverse the negative results obtained in the first half of the paper, based on the standard panel data analysis.

**Figure 2. Trends in Industry average output and capital: US. (1995=100).**



Notes: y = real output, kst = total capital services, ksi=ICT capital services, ksni = non-ICT capital services.

There has been a widespread application of time-series methods applied to panel data in recent years. Examples include the analysis of growth and convergence (Lee, Pesaran and Smith, 1997 and Nerlove, 2000), price determination (Ashworth and Byrne 2001), and savings and investment models (Moon and Philips 1998)<sup>5</sup>.

<sup>5</sup> For a discussion see Baltagi (2001).

Various procedures have been developed in order to deal with dynamic panel data sets. The analysis in the remainder of this paper is based on the Pooled Mean Group (PMG) estimator discussed in Pesaran et al. (1999). The PMG estimator extends the error-correction modelling framework to the panel dimension by imposing homogeneity restrictions on the long-run parameters and deriving the error correction coefficient and the other short-run parameters of the model by averaging across groups. An alternative technique, the Mean Group estimator, also discussed in Pesaran et al. (1999), involves simply the estimation of separate equations for each industry and the computation of the mean of the estimates, without imposing any constraint on the parameters. However, if some parameters are the same across groups efficiency gains are made by taking this into account. The homogeneity of the short-run coefficients in the PMGE is tested against the MG estimates using the Hausman test.

Assuming the maximum lag to be 1, we can write the error correction form of equation (4) as follows:

(5)

$$\Delta q_{it} = \lambda_i (q_{it-1} - \phi_0 - \phi_1 l_{it-1} - \phi_2 k_{it-1}^N - \phi_3 k_{it-1}^I) + \delta_{1i} \Delta l_{it} + \delta_{2i} \Delta k_{it}^N + \delta_{3i} \Delta k_{it}^I + v_{it}$$

where  $\lambda_i$  is the error correction term. Imposing the same long run coefficients in a production function framework implies that in the long run the returns to the factor inputs will be the same across industries, which is a reasonable theoretical assumption. Compared to standard panel data techniques (fixed/random effect or first difference estimator) the PMG can account for industry heterogeneity, by allowing different short-run dynamics in each cross sectional unit.

Before presenting the results from the PMG estimation, we run stationarity and cointegration tests to check whether we are indeed dealing with a non-stationary panel. If our variables are non-stationary we can be confident of the fact that previous results based on simple panel data techniques are inconsistent. This would further justify the use of a technique that allows for short-run dynamic adjustments. A brief discussion on the testing procedure and the results are presented in the next section.

## **6 Nonstationarity and cointegration**

A large literature has recently developed on unit roots and cointegration tests for panel data (Banerjee 1999). The emphasis of the various contributions is to combine information from the time series and the cross section dimensions and so increase the power of pure time-series based tests. Drawing on this literature, we apply two tests for unit roots, the Im et al. (2002) test (IPS) and the test developed by Hadri (2000).

The IPS test is based of the null of a unit root in panel data, against the alternative of stationarity. It is an extension of the test devised by Levin and Linn (1992) and it is based on an average Dickey Fuller (DF) (Dickey-Fuller 1979) or Augmented Dickey Fuller (ADF) test for each cross-sectional unit. Hadri (2000) proposes a different test with a null of stationarity and the alternative of a unit root in the panel data. Given the well known low power of standard unit roots tests, Hadri (2000) recommends to test for both null hypotheses to distinguish “*..series that appear to have a unit root and series for which we are unsure whether they are stationary or integrated*”.

The results from the two testing procedures are presented in Table 2. The three versions of the Hadri (2000) test allow respectively for homoskedastic (Hadri 1), heteroskedastic (Hadri 2) and serially dependent disturbances (Hadri 3). All tests are



based on demeaned data, in order to account for the common time period effect, and they also include a time trend. The IPS test results show that the null hypothesis of the presence of a unit root can be rejected at the 5% significance level for employment, while it can be rejected at the 10% significance level for ICT and non ICT capital. The three versions of the Hadri test, on the other hand, reject the null of stationarity for all variables. We also have to remember that the formulation of the alternative hypothesis in the IPS test allows for some of the cross sectional units to contain a unit root <sup>6</sup>. Therefore we have a reasonably strong evidence of the presence of unit roots in our data.

**Table 2**

***Test of the Null of the Presence of a Unit Root and of the Null of stationarity  
(1976-1999, 31 US industries, 24 UK industries).***

	IPS test	Hadri (1)	Hadri (2)	Hadri (3)
<i>Output</i>	0.835 (0.202)	40.508* (.000)	31.576* (.000)	21.713* (.000)
Employment	-2.074* (0.019)	43.096* (.000)	39.757* (.000)	22.482* (.000)
Non-ICT capital	-1.393 (0.082)	63.484* (.000)	50.663* (.000)	32.798* (.000)
ICT capital	-1.585 (0.056)	71.322* (.000)	56.173* (.000)	36.818* (.000)

P values in brackets. A “\*” in the IPS test signifies rejection of the null of unit roots at the 5% level of significance. A”\*” in the Hadri tests signifies rejection of the null of stationarity at the 5% level of significance.

The next step is to investigate whether some linear combination of these variables can be described as stationary. The tests for cointegration developed by Pedroni (1999) are the panel analogue of Engle and Granger (1987) test for the pure

<sup>6</sup> This feature of the IPS test is the main extension of the Levin and Lin (1992) test, where the

time series case. As such, they are based on the residual of the static (cointegrating) regression and they test the null of no cointegration<sup>7</sup>. In our specific case we want to test for the presence of the following cointegrating relationship:

$$(6) \quad q_{it} = \eta_{0i} + \eta_{1i}l_{it} + \eta_{2i}k_{it}^N + \eta_{3i}k_{it}^I + \omega_{it}$$

where lower case variables denote logarithms. The hypothesis of cointegration implies that there exists a long-run relationship between output and employment, ICT and non-ICT capital.

Pedroni (1995, 1999) develops seven cointegration tests for panel data, four for the within model and three for the between model. The former, also called panel cointegration statistics, are based on pooling the autoregressive coefficient across different members for the unit root tests on the estimated residuals, while the latter, also called group mean panel cointegration statistics, are based on estimators that simply average the individually estimated coefficients for each member  $i$ . Of the seven tests we report the Panel ADF statistics and the group ADF statistics. As the name suggests these tests are analogous to the augmented Dickey–Fuller  $t$ -statistic. Pedroni (1997) shows that the ADF-based tests perform best in small samples, which justifies our choice (see also Sarantis and Stewart 2001). The group ADF test is likely to be more accurate in our specific case, given the heterogeneity of our data set. However, we present the two versions of the test for comparison purposes.

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alternative hypothesis assumes that all series are stationary (Banerjee 1999).

<sup>7</sup> As with unit roots tests, the application of cointegration test to panel data increases the power of the test especially when the series are of moderate length. Panel cointegration techniques are intended to pool information regarding common long-run relationship from across the panel while allowing the short-run dynamics and fixed effect to be heterogeneous across units.

**Table 3**

*Pedroni (1999) panel cointegration test*

**(1976-1999, 31 US industries, 24 UK industries).**

	Standard	With heterogeneous trend
Panel ADF	-4.174*	-7.747*
Group ADF	-4.257*	-6.495*

The number of lag truncations used in the calculation of the Pedroni statistics is 3. These are one-sided tests with a critical value of  $-1.64$ . The critical values for the mean and variances of each statistic were obtained from Pedroni (1999, table 2). The panel statistics were computed using an algorithm kindly provided by Pedroni.

The results presented in table 3 show that the null of no cointegration can always be rejected implying that there exists a long-run relationship between output and inputs. This in turn means that when accounting for the long run relationship between variables we introduce an important source of information into the analysis, information that is normally lost when estimating in first difference. This long-run information is going to be part of the estimation procedure presented in the next section.

**7 Dynamic panel data estimation.**

In this section we present the results based on the PMG estimator. As in the tests above, the estimation is based on demeaned data, in order to account for common time-period effects across industries. The lag order was chosen in each industry by the Schwarz Bayesian criterion subject to a maximum lag of 3. Then, using these SBC – determined lag orders, homogeneity was imposed. As starting values for the coefficients of the production function we used the factor shares implied by the

growth accounting framework (see table 1). However the results are robust to different starting values and different lag orders.

Table 4 also presents result for the test of the assumption of long-run homogeneity of our coefficients using individual and joint Hausman tests, based on the null of homogeneity.

**Table 4**  
*Pooled Mean Group Estimates (Pesaran, Shin and Smith 1999).*  
**(1976-1999, 31 US industries, 24 UK industries).**

Variable	Production Function Estimates	Hausman test
Employment	0.862* (0.014)	2.67 (0.10)
Non-ICT capita	0.113* (5.762)	0.00 (0.97)
ICT capital	0.058* (0.006)	0.37 (0.54)
Joint Hausman test		4.77 (0.19)
Error Correction coeff.	-0.823* (-0.09)	

A “\*” denotes rejection of the null at 5% level of significance.

The results from the estimation of the production function show a high and significant long run impact of ICT on output. The estimated coefficients is considerably higher than the growth accounting average share (equal to 0.0286 across

the sample), showing that the growth accounting framework understates the contribution of ICT capital to output growth and that there are likely to be increasing returns from the accumulation of this particular form of capital. Over the entire sample these results suggest that the growth in ICT capital could account for about 40% of output growth compared to the 20% based on the Tornqvist index growth accounting calculation mentioned in section 3 above.

As for the other inputs, the labour coefficient is higher than the one assumed by growth accounting, while the non-ICT capital is lower. Overall, returns to scale are approximately constant. The error correction coefficient is significant and has the expected sign, showing that approximately 80% of the gap is removed in each year. This suggests a fast dynamic adjustment of the returns to the factors of production to their long run values. The Hausman test does not reject the null of poolability of the long-run coefficients at the 5% level of significance.

One limitation of this technique is that we cannot test whether the US long run coefficients are significantly different from those for the UK. The individual country results were not found to be robust to either the lag structure or the starting values, and this is probably due to the small sample size for each individual. However the Hausman test does not reject the assumption of long run homogeneity across all industries in the sample therefore it does not appear that we are imposing too strong an assumption on the data. Moreover, it is likely that in the long run production function coefficients will converge across countries, especially when the two countries are very close in terms of technology use and development.

The main conclusion from this section of the analysis is that the PMG estimator has produced results that are in line with prior expectations on the impact of ICT capital on output growth. The results have confirmed the presence of positive

returns to ICT capital and suggest the possibility that standard growth accounting exercises may understate the contribution of ICT to output growth and TFP. The gain from using this technique, as opposed to the standard panel data analysis, is to allow for heterogeneous dynamic adjustments towards a common long run equilibrium. The specification used in the empirical analysis has proved to be a better representation of the way ICT capital investments are affecting both manufacturing and non-manufacturing industries. The heterogeneous way in which ICT capital has spread across the different sectors of the economy, and the way in which it is still growing suggests that we are dealing with a very dynamic process, whose features are better captured in the method employed here.

## **7. Concluding remarks**

This paper has presented new evidence on the impact of ICT investment on output growth, using industry data for the USA and the UK. Starting from the standard panel data framework, we could not find any positive and significant returns to ICT capital, hence corroborating the results of the existing literature based on similar data sets and a similar technique (Stiroh 2002b). However, by going beyond the standard panel data production function estimation, using a different econometric methodology that specifically accounts for industry heterogeneity and for the time series nature of the data, we do obtain a positive coefficient on ICT capital in a production function framework. This coefficient was significantly greater than the one implied by growth accounting normally employed in evaluating the impact of ICT capital on output growth. Thus it suggests that there is more to ICT than that calculated through ICT capital deepening in a growth accounting model and this is consistent with the notion

of ICT as a general purpose technology which increases the long run growth rate (Helpman 1998).

Previous contributions to this literature suggest there may be an inconsistency between micro studies based on firm level data which frequently imply large contributions from ICT to productivity growth and more macro evidence based on industry data where such effects have been difficult to identify. The main contribution of this paper has been to show that there may not in fact be an inconsistency between the macro and micro evidence.

Showing a positive contribution from ICT capital using aggregate industry data is of course only the start of the story. Further analysis is required on the process by which this new technology has altered the production process, the links with organisational changes and with other inputs such as skilled labour. These issues will challenge future work on the relationship between ICT and growth.

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