Is there an ICT impact on TFP?

A heterogeneous dynamic panel approach*.

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Abstract

Using a new set of industry data for the US and the UK and an appropriate econometric approach, this paper provides new evidence on the impact of Information and Communication Technology (ICT) on Total Factor Productivity (TFP). We compare the results from standard panel data techniques with an heterogeneous dynamic panel data estimation method. The traditional industry panel data analysis fails to find a positive impact of ICT on output/TFP growth. This paper argues that this is due to heterogeneity across industries, particularly in the time dimension. The alternative technique we use, which allows for industry specific dynamics, 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 vigorous 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[1]. 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 terms of network spillovers. Since the market does not remunerate returns from

[1] See e.g. Jorgenson and Stiroh, 2000, Oliner and Sichel, 2000, 2002, for US evidence, Colecchia and Schreyer, 2001, for OECD countries and both Oulton, 2002, and Cette et al. 2002, for single country studies.

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, 2000, 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 that covers all sectors within this aggregate; industry level data represent 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, shows 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 25 years of observations for each cross section, the dynamic pattern of the data cannot be neglected. The simple Ordinary Least Squares (OLS) approach, based on the assumption of stationarity of all the variables included in the regression and cross-industry coefficient homogeneity can produce highly misleading results (Pesaran and Smith 1995, Im et al. 2002,). Therefore the main body of the empirical analysis will employ a methodology that accounts for heterogeneous dynamic panels (Pesaran et al., 1999), after testing for stationarity and cointegration.

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 -7). 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 9 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) $$Q_{it} = A_{it}F(K_{it}, L_{it})$$

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 composed 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 (Jorgenson et al. 1987) given by:

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

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. Using similar notation to above and assuming a Cobb Douglas functional form, given by:

(3) $$Q_{it} = A_{it}L^{\alpha}_{it}K^{\beta}_{it}$$

we can re-write equation (3), after taking logs and first differences and allowing for the two types of capital, as follows:

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

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: $(1 - s_{li(t,t-1)})s^{I}_{i\ (t,t-1)}$, as in equation (2). 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 with 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 readily 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[2]. Thus it excludes sectors within the public domain in at least one country where output measurement presents severe difficulties. The list of sectors was dictated largely by the availability of investment series required to estimate ICT and non-ICT capital stocks.

[2] **US Industry List:** see footnote to Figure 1, section 5. **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

Output is real value added rather than the theoretically preferable gross output measure (Stiroh, 2002) due to the lack of reliable data for intermediate inputs in UK non-manufacturing industries. 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. Indices 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

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other transport equipment; and motor vehicles sales & repair with wholesale trade. In addition all transport sectors are combined into a single group (24 industries).

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, 1976-2000.

	Output	Labour	ICT capital	Non-ICTcapital	TFP
			A. Pooled sample		
Growth rate	2.28	-0.06	17.61	2.05	1.22
Value Added shares	-	69.48	2.92	27.6	-
			B. USA		
Growth rate	2.87	0.88	15.31	2.21	1.17
Value Added shares	-	70.42	3.48	26.10	-
			C. UK		
Growth rate	1.51	-1.29	20.55	1.85	1.29
Value Added shares	-	68.25	2.19	29.56	-

4. Econometric Results: the basic model

In this section we present the results based on standard panel data estimation to check if the evidence 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, where industry specific dummies are included in the equation in levels, and a specification in first differences[3]. The data have been pooled across the two countries, while the introduction of interactive dummies allows for different coefficient estimates in the US and the UK.

[3] All variables were indexed to equal 100 in the initial year, 1976.

Time dummies have been added to all specifications in order to account for common shocks that might have affected industry productivity. For comparison purposes we also present, in appendix table A.1, the results based on a specification without time dummies. The introduction of time dummies generally reduces the impact of ICT capital on productivity in the standard panel data analysis (Stiroh 2002b). Given that ICT capital has been characterised by a high rate of growth over the last 10 years, it is likely that the time dummies capture part of this trend. However we take the view in this paper that results are unconvincing if they do not take account of the common factor problem.

Table 2 presents the results from the estimation of equation (4). 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[4].

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 private returns on ICT capital are negative or these are positive but negative external effects outweigh

[4] When the time dummies are excluded, the ICT coefficient is positive and significant in the specification in levels (see Appendix table A.1). However, this cannot be taken as evidence of a significant ICT impact since output is trended. ICT capital may be merely picking up this trend.

any positive private benefits from investing in this type of capital. Similar results for US manufacturing results were found by Stiroh (2002a)[5].

Table 2.

Panel Regressions, Production Function estimation.

(1976-2000, 31 US industries, 24 UK industries).

Variables	Fixed effect estimator Dependent variable: q_{it}		First difference estimator Dependent variable: Δq_{it}	
		Pooled coefficient		
l_{it}	0.333* (0.027)	-	0.468* (0.071)	-
k_{it}^N	0.362* (0.033)	-	0.233* (0.055)	-
k_{it}^I	-0.048* (0.098)	-	-0.026 (0.017)	-
		US Coefficients		
l_{it}	-	0.382* (0.059)	-	0.648 * (0.107)
k_{it}^N	-	0.141* (0.023)	-	0.187* (0.086)
k_{it}^I	-	-0.078* (0.013)	-	-0.031 (0.022)
		UK coefficients		
l_{it}	-	0.348* (0.033)	-	0.290* (0.081)
k_{it}^N	-	0.311* (0.036)	-	0.285* (0.069)
k_{it}^I	-	-0.047* (0.009)	-	-0.019 (0.022)
Adjusted R^2	0.869	0.866	0.283	0.295

Notes: standard errors in parentheses. Standard errors are heteroscedastic consistent. *Refers to a significant coefficient at 95% confidence 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] This results are also consistent with the fixed effect estimates in McGuckin and Stiroh (2002), table 4, p. 53. See also Berndt and Morrison (1995) and Kiley (2001).

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 such as ICT (Bresnahan and Trajtenberg 1995, 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).

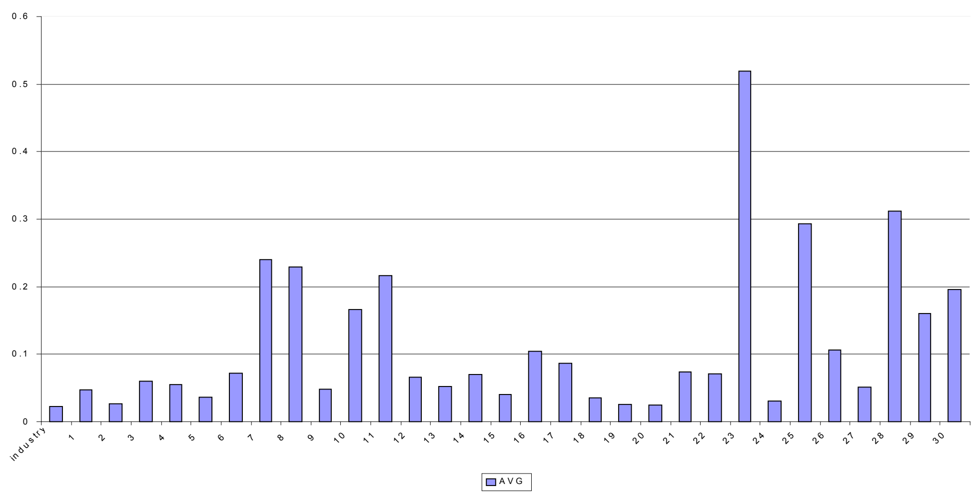
To explore these results further we experimented with a number of alternative specifications, for example including the growth of total capital and the ICT capital share as regressors to assess the relationship between the intensity of use of ICT and the rate of growth of TFP. This yielded a positive 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. More plausible results were obtained with dynamic specifications employing lagged values of the dependent and explanatory variables. 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.[6]

[6] Results are available from the authors on request.

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 and the time series properties of the data. First, the data show a high degree of heterogeneity, particularly in the ICT capital services. Figure 1 shows the average ICT to total capital ratio (ICT/TK) by industry for the US (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. These large differences are unlikely to be adequately captured by the mere inclusion of time invariant industry dummies.

Figure 1: ICT/TK in the US

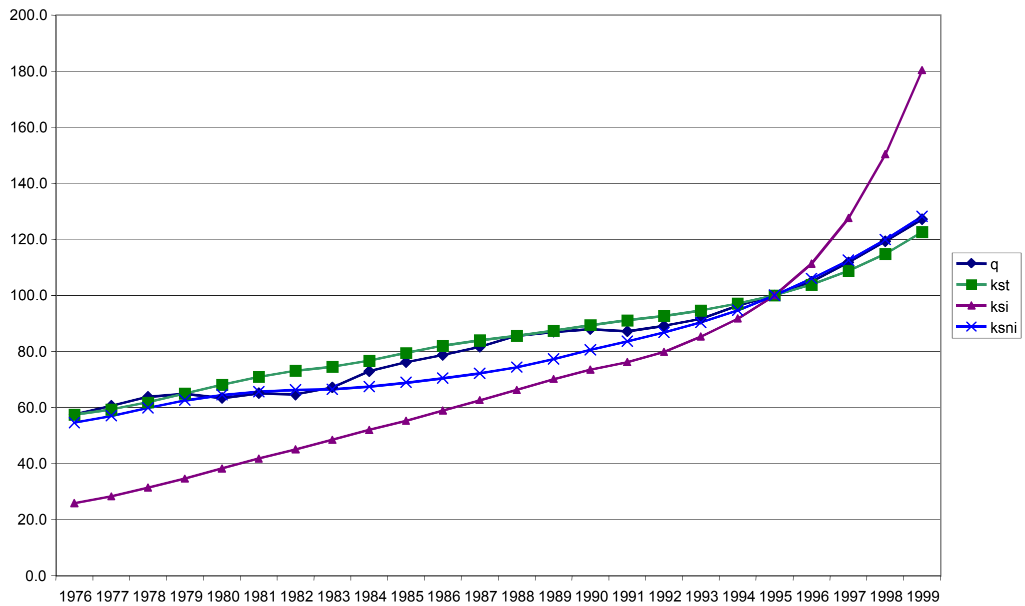


1=mining, 2=electricity, gas and water, 3=coal and petroleum products, 4=chemicals, 5=rubber and plastics, 6=basic metals, 7=metal products, 8=office and mechanical engineering, 9= electrical engineering, 10=motor vehicles, 11=other transport equipment, 12=instrument engineering, 13=textiles, clothing 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

Second, and related to this issue, 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.

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



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

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 is 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 25 years of observations for each industry, we introduce a substantial time dimension and heterogeneity in the analysis. If our variables are non-stationary we can be confident of the fact that previous results based on simple panel data techniques are inconsistent.

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.

Following these considerations we present, in the next section, stationarity and cointegration tests while in section 7 we discuss an alternative econometric technique that specifically accounts for heterogeneity and the time series properties of the data (Pesaran et al. 1999).

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)[7].

The results from the two testing procedures are presented in Table 3. 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. However, the formulation of the

[7] The IPS test is based on 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)

alternative hypothesis in the IPS test allows for some of the cross sectional units to contain a unit root [8]. The three versions of the Hadri (2000) test allow respectively for homoskedastic (Hadri 1), heteroskedastic (Hadri 2) and serially dependent disturbances (Hadri 3). All versions of the test reject the null of stationarity for all variables. Therefore we have a reasonably strong evidence of the presence of unit roots in our data.

Table 3.

Test of the Null of the Presence of a Unit Root and of the Null of stationarity.

(1976-2000, 31 US industries, 24 UK industries).

Variable	IPS test	Hadri (1)	Hadri (2)	Hadri (3)
q_{it}	0.835 (0.202)	40.508* (0.000)	31.576* (0.000)	21.713* (0.000)
l_{it}	-2.074* (0.019)	43.096* (0.000)	39.757* (0.000)	22.482* (0.000)
k_{it}^{N}	-1.393 (0.082)	63.484* (0.000)	50.663* (0.000)	32.798* (0.000)
k_{it}^{I}	-1.585 (0.056)	71.322* (0.000)	56.173*(0.000)	36.818* (0.000)

Notes: 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.All tests presented in Table 3 are based on cross-sectionally de-meaned data in order to account for the common factor problem. Using the raw data does not alter the results.

The next step is to investigate whether a linear combination of these variables can be described as stationary, i.e. whether the there exists a stationary long run production function relationship. For this purpose we refer to Pedroni (1997, 1999)[9] and we report, in table 4, the Panel ADF statistics and the group ADF statistics.

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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"*.

[8] This feature of the IPS test is the main extension of the Levin and Lin (1992) test, where the alternative hypothesis assumes that all series are stationary (Banerjee 1999).

[9] 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

Pedroni (1997) shows that the ADF-based tests perform best in small samples, which justifies our choice (see also Sarantis and Stewart 2001).

Table 4.

Panel cointegration test.

(1976-2000, 31 US industries, 24 UK industries).

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

Notes: the number of lag truncations used in the calculation of the Pedroni statistics is 3. These are one-sided tests with ah 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 4 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. The Pooled Mean Group estimator

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

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.

Byrne 2001), and savings and investment models (Moon and Philips 1998)[10]. 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 (MG) 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 test of the homogeneity of the long-run coefficients is provided by an Hausman test. This is based on the null that the two set of coefficients generated by the PMG and MG estimators are not statistically different. Under the null hypothesis this statistic is asymptotically distributed as a $\chi^2(p)$, where p is the number of parameters.

To illustrate the method, we start with the following long-run relationship:

$$(5)\quad q_{it} = \theta_{0i} + \theta_{1i} l_{it} + \theta_{21} k_{it}^{N} + \theta_{31} k_{it}^{I} + u_{it}$$

For simplicity, assuming a maximum lag order of one, we can re-write equation (5) as an autoregressive distributed lag (ARLD) (1,1,1,1) as follows:

$$(6)\quad q_{it} = \mu_{it} + \delta_{10i} l_{it} + \delta_{11i} l_{i,t-1} + \delta_{20i} k_{it}^{N} + \delta_{21i} k_{i,t-1}^{N} + \delta_{30i} k_{it}^{I} + \delta_{31i} k_{i,t-1}^{I} + \lambda_i q_{i,t-1} + \varepsilon_{it}$$

Rewriting equation (6) in an error correction form yields:

[10] For a discussion see Baltagi (2001).

$$(7)\ \Delta q_{it} = \phi_i (q_{i,t-1} - \theta_{0i} - \theta_{1i} l_{it} - \theta_{2i} k_{it}^N - \theta_{3i} k_{it}^I) - \delta_{11} \Delta l_{it} - \delta_{21} \Delta k_{it}^N - \delta_{31} \Delta k_{it}^I + \varepsilon_{it}$$

where:

$$\theta_{0i} = \frac{\mu_i}{1-\lambda_i},\ \ \theta_{1i} = \frac{\delta_{10i} + \delta_{11i}}{1-\lambda_i},\ \ \theta_{2i} = \frac{\delta_{20i} + \delta_{21i}}{1-\lambda_i},$$

$$\theta_{3i} = \frac{\delta_{30i} + \delta_{31i}}{1-\lambda_i},\ \ \phi_i = -(1-\lambda_i)$$

Imposing the same long run coefficients in a production function framework implies that in the long run the elasticities of output with respect to factor inputs will be the same across industries. Industry heterogeneity is accounted for by allowing different short-run dynamics in each cross sectional unit.

The specification in equation (7) merely illustrates the (ARLD) (1,1,1,1) case but implementing the method in practice requires specifying the most appropriate lag order for each industry. The estimating programme[11] permits manual setting of lag orders or automatic specification using a range of information criteria.

8. Dynamic panel data estimation.

In this section we discuss the results based on the PMG estimator, as shown in Tables 5 - 7. The results below are based on lag orders for each industry chosen by the Schwarz-Bayesian information criterion (SBC) 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 information criteria used to specify the lag orders.

Table 5 presents the long-run coefficients, the error correction term and the Hausman test. The estimation was carried out using both the raw data and on the cross-sectionally de-meaned data, equivalent to including time dummy variables in standard panels.

Table 5.

Pooled Mean Group Estimates .

(1976-2000, 31 US industries, 24 UK industries).

Variable	Raw data	*Hausman test*	De-meaned data	*Hausman test*
l_{it}	0.675* (0.016)	*0.840 (0.360)*	0.841* (0.016)	*2.480 (0.120)*
k_{it}^{N}	0.155* (0.016)	*2.250 (0.130)*	0.104* (0.017)	*2.240 (0.130)*
k_{it}^{I}	0.055* (0.002)	*3.430 (0.060)*	0.066* (0.004)	*0.148 (0.220)*
Joint Haus. test		*4.720 (0.190)*		*4.470 (0.210)*
ECM	-0.480* (0.061)		–0.825* (0.092)	

Notes: standard errors in parentheses. * Denotes rejection of the null at 5% level of significance.

Both sets of results show a high and significant long run impact of ICT on output. The estimated coefficients are 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. Also note that using cross-sectionally de-meaned data slightly increases the ICT coefficient. This contrasts with the evidence presented in section 4 and with the

[11] Downloaded from web-site **:** http://www.econ.cam.ac.uk/faculty/pesaran/jasa.exe .

existing studies (Stiroh 2002a and 2002b). It also confirms our a priori view that the standard panel data analysis imposes too many restrictions on the data, hence yielding potentially misleading results.

As for the other inputs, the labour coefficient is higher that the one assumed by growth accounting, while the non-ICT capital is lower, particularly when we use de-meaned data. This can be the result of unmeasured input utilisation, particularly in the non-ICT capital, and/or could reflect an omitted variable problem, such as human capital and organisational changes. Overall, returns to scale are approximately constant. The error correction coefficient is significant in both sets of results and has the expected sign. Compared to the raw data estimates, the de-meaned data results imply a much faster speed of adjustment, suggesting that approximately 80% of the gap is removed in each year. The Hausman test does not reject the null of poolability of the long-run coefficients at the 5% level of significance.

Multiplying the estimates of the elasticity in table 5 by the average output to capital ratio in the US and in the UK is a "back-of-the-envelope" measure of the marginal returns to the two capital inputs. This suggests that the marginal returns to ICT and non-ICT capital both equal 18% when the calculation is based on the raw data estimates[12]. When using the estimates based on the de-meaned data the returns to ICT are 22%, significantly higher than the 12% returns to non-ICT capital[13]. These calculations are based on the assumption that the long-run elasticities in the two countries are equal. Although this assumption is not rejected by our data, it is possible that single country estimates would reveal some differences. The next section of the paper will attempt to deal with this issue.

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[12] The standard errors are 0.007 for ICT capital and 0.018 for non-ICT capital.
[13] The standard errors are 0.013 for ICT capital and 0.020 for non-ICT capital.

8.2 Individual country estimates

Table 6 and 7 show the country by country results. As for the pooled sample, we present the estimates based on the raw data and on the cross-sectionally de-meaned data[14]. The country results do not show large differences in the labour and non-ICT capital coefficients, while they imply a larger long-run impact of ICT on output in the USA, compared to the UK. This is not surprising given that the USA is the leader in adopting ICT technology and so firms have had more time to reap the full benefits of their investments. When using de-meaned data the ICT coefficient in the USA becomes twice as high as in the raw data specification. This result even if consistent with existing estimates (McGuckin and Stiroh 2002, table 4) is suspiciously high. It would in fact imply marginal returns to ICT capital of 51% (with a standard error of 0.040). The estimates based on the raw data are more sensible, suggesting marginal returns to ICT capital of 28% (0.011). In both cases the returns to ICT are significantly higher than the returns to non-ICT capital (40% in the demeaned data estimates and 16% in the raw data estimates).

Based on the raw data estimates, the results for the UK imply marginal returns to ICT capital of approximately 20%, significantly lower than in the USA, but not significantly different for non-ICT capital (estimated to be 21%). The de-meaned data results give a negative value for the ICT capital coefficient.

[14] Note that the raw data estimates are directly comparable to the pooled sample results, unlike the de-meaned estimates. This follows from the fact that the de-meaning procedure in table 4 and 5 is based on a different number of cross-sections.

Table 6.

USA Pooled Mean Group Estimates.

(1976-2000, 31 industries).

Variable	Raw data	Hausman test	De-meaned data	Hausman test
l_{it}	0.604* (0.034)	1.040 (0.310)	0.563* (0.035)	0.000 (0.950)
k_{it}^{N}	0.139* (0.024)	2.030 (0.150)	0.348* (0.040)	3.040 (0.008)
k_{it}^{I}	0.097* (0.004)	2.180 (0.140)	0.180* (0.014)	0.230 (0.630)
Joint Haus. test.		3.670 (0.300)		3.340 (0.340)
ECM	-0.489* (0.080)		-0.905* (0.081)	

Notes: standard errors in parentheses. * Denotes rejection of the null at 5% level of significance.

Table 7.

UK Pooled Mean Group Estimates.

(1976-2000, 24 industries).

Variable	Raw data	Hausman test	De-meaned data	Hausman test
l_{it}	0.665* (0.019)	0.070 (0.790)	0.515* (0.025)	1.910 (0.170)
k_{it}^{N}	0.175* (0.019)	0.720 (0.400)	0.314* (0.014)	0.920 (0.340)
k_{it}^{I}	0.053* (0.002)	0.930 (0.330)	-0.013* (0.005)	0.020 (0.880)
Joint Haus. test		3.950 (0.270)		4.050 (0.260)
ECM	-0.505*(0.108)		-0.730* (0.146)	

Notes: standard errors in parentheses. * Denotes rejection of the null at 5% level of significance.

Overall, the country by country results do suggest higher returns to ICT capital in the USA than in the UK. However, some caution is needed when looking at the individual country estimates, as they are likely to be affected by a small sample size problem. When we split the data by country we are unlikely to reduce the degree of heterogeneity given the similarity in the industry lists in the two countries. On the other hand we approximately halve the number of cross-sectional observations, hence reducing the efficiency of our estimates. Therefore, while the country estimates give an indication of the comparative importance of ICT capital, we do not think that they can be used to draw definite conclusions on the actual size of the long run output-ICT elasticities and marginal returns.

In favour of the pooled sample results is the fact that the Hausman test does not reject the assumption of long run homogeneity across all industries in the sample and therefore it does not appear that we are imposing too strong an assumption on the data. Although growth accounting estimates do show differences in elasticities across industries, these ‘point’ estimates may not be significantly different from each other. The fact that pooling passes the Hausman test, in the words of Pesaran et al. (1999), suggests that pooling is not in ‘gross violation’ of the data. Moreover, it is likely that, in the long run, production function coefficients will converge in the same industries across countries, especially when the two countries are very close in terms of technology use and development.

9. Concluding remarks

The main conclusion from this paper 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 the PMG estimator, 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 presented in section 5 is likely 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. The results using this approach suggest 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).

The analysis has also focused on the inadequacy of the standard panel data techniques when using industry data set characterised by a long time dimension and a relatively small number of cross sections. First, we are not dealing with a proper panel, where we observe the same unit, such as a company or an individual, through time, but we are analysing industries whose structure may change over time (Vecchi 2000). Secondly, the long time dimension of these types of data sets requires an investigation of the dynamic properties of the series used in the estimation, in order to avoid spurious results. Imposing the same coefficients across all industries and not allowing for any short-run dynamic adjustments imply strong restrictions on the data that should at least be tested.

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. In addition, considerations related to the endogeneity of the inputs should also be addressed. These issues will challenge future work on the relationship between ICT capital and growth.

Appendix A.

Table A.1.

Panel Regressions, Production Function estimation, 1976-2000.

(1976-2000, 31 US industries, 24 UK industries).

Variables	Fixed effect estimator Dependent variable: q_{it}		First difference estimator Dependent variable: Δq_{it}	
	Pooled coefficient			
l_{it}	0.305* (0.024)	-	0.579* (0.067)	-
k_{it}^N	0.360* (0.025)	-	0.194* (0.055)	-
k_{it}^I	0.066* (0.005)	-	-0.073*(0.016)	-
	US Coefficients			
l_{it}	-	0.272* (0.041)		0.772* (0.077)
k_{it}^N	-	0.469* (0.044)	-	0.092 (0.087)
k_{it}^I	-	0.086* (0.007)	-	-0.067* (0.020)
	UK coefficients			
l_{it}	-	0.174* (0.031)	-	0.367* (0.085)
k_{it}^N	-	0.386* (0.030)	-	0.294* (0.069)
k_{it}^I	-	0.035* (0.007)	-	-0.083* (0.024)
Adjusted R^2	0.932	0.880	0.210	0.229

Notes: standard errors in parentheses. Standard errors are heteroscedastic consistent. * Refers to a significant coefficient at 95% confidence level. No. industries = 55, industry fixed effects included in the levels equations and a UK intercept dummy in the first difference specification.

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