THE DYNAMIC IMPACT OF ICT SPILLOVERS ON COMPANIES' PRODUCTIVITY PERFORMANCE*.

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Abstract

Using company account data for the US and four European countries this paper analyses the impact of ICT spillovers on companies' performance. We use different definitions of spillovers to account for inter and intra-industry spillover effects, as well as assessing the presence of spillovers from the US to Europe. We also look at the possibility that spillovers might take some time to materialise, by comparing their short and long run impact. Our results show that ICT spillovers affect productivity differently in the US and in Europe in the short run but in the long run such differences are less profound.

JEL classification: C23, D24, D62

Keywords: R&D and ICT capital, dynamic spillovers, panel unit root tests, panel cointegration tests.

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INTRODUCTION

The United States economy has experienced a surge in productivity growth in the second half of the 1990s, whereas over the same period the performance of the European Union has worsened, with both labour and total factor productivity (TFP) growth lagging behind the United States (O'Mahony and van Ark 2003). Various explanations have been provided for this phenomenon, such as cyclical mismeasurements of inputs or differences in national accounts methodology (Gust and Marquez 2004). However the different speed of adoption and diffusion of information and communications technology (ICT) appears to play an increasingly important role. The literature to date has emphasised the considerable impact on output growth from ICT capital deepening in the US (see e.g. Oliner and Sichel 2000, Jorgenson and Stiroh 2000 and Stiroh 2002). Significant but considerably lower impacts from ICT capital deepening have been found for European countries (Colecchia and Schreyer 2001).

More recently the debate has moved beyond the narrow focus on ICT capital deepening to consider the nature of this new technology and its relationship to complementary investments. ICT is now seen as an example of a general purpose technology (GPT), which requires substantial investment in complementary capital or new intermediate inputs, such as training and work re-organisation (Aghion and Howitt 1998). This means that the payoffs in terms of measured output can be delayed. Given Europe's later adoption of ICT technology, compared to the US, more time might be needed to observe an increase in productivity (Daveri 2002).

In this paper we compare performance in the US and Europe by analysing productivity growth at the micro-economic level. Our investigation is based on company accounts data (Compustat) and it includes the US and four European countries (UK Germany, France and the Netherlands). The main focus of the paper is to ascertain the presence of ICT spillovers and how they have affected companies' productivity performance. The GPT story stresses the importance of spillovers and the different ways in which they originate. For example a new technology, like ICT, is likely to improve productivity both within the same company/industry and across different industries (Bresnahan and Trajtenberg 1995), as well as improving the efficiency of transactions among firms (Rowlatt 2001, Criscuolo and Waldron 2003).

While the theoretical importance of ICT spillovers has been widely recognised, the empirical evidence only offers few examples (Brynjolfsson and Hitt 2000, Van Leeuwen and van der Wiel 2003), probably because of the difficulty in measuring spillover effects. In this paper we begin by using a traditional approach which consists of modelling the output of a single firm as a function of its own inputs and an index of aggregate activity (Helpman 1984, Caballero and Lyons 1989, 1990, Vecchi 2000). Similarly to Jones (1968) we assume that spillovers or external economies are related to the scale of the industry ICT input and are external to the decisions taken by any firm so as to retain the perfectly competitive nature of the model. Therefore we will evaluate whether companies' productivity performance is affected by the total stock of ICT capital within each industry. Additionally we investigate whether different ICT aggregates produce different results, by grouping companies according to their intensity of using/producing ICT (van Ark et al. 2002). Companies with similar ICT adoption patterns are likely to face similar problems and to learn from each other's experience (Aghion and Howitt 1998). Finally we also look at the possibility of ICT knowledge to spillover from the leader (the US) to the follower country (Europe).

The paper also looks at the spillover issue from a different perspective, i.e. it attempts at investigating its dynamic impact on productivity. Spillovers have been implicitly assumed to be a static phenomenon and only contemporaneous spillover effects have been analysed in the related literature. However, as Sena (2004) has recently pointed out, a problem with this approach is that it ignores the possibility that spillovers can take more time to be incorporated into new products and diffused throughout the industrial sector. Therefore particular attention will be devoted to the short run and the long run impact of ICT spillovers on companies' productivity performance, using dynamic panel data analysis (Pedroni 1999).

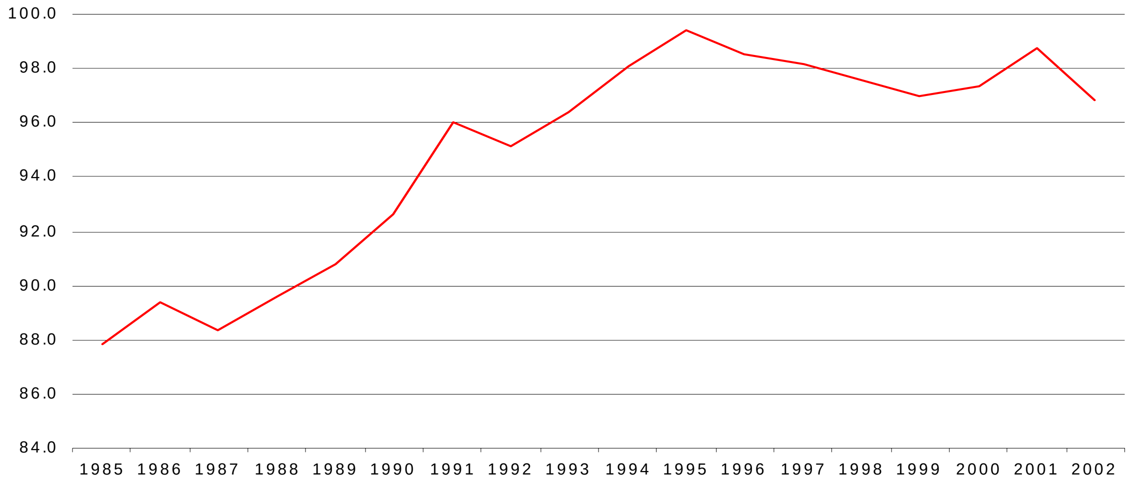
The following section presents an overview of the productivity trends in the US and Europe, comparing macro and company data. Section 2 discusses the main implications of ICT as a General Purpose Technology (GPT) and as a potential source of spillovers. Section 3 describes the data sources while section 4 presents the model used in the empirical analysis. Our results are presented and discussed in section 5. Section 6 concludes the paper.

1. THE SLOWDOWN IN EUROPEAN PRODUCTIVITY GROWTH: AN OVERVIEW.

Since the mid 1990s average growth rates of real GDP, labour productivity and total factor productivity in the European Union fell behind those in the United States. Some European countries like the UK, Ireland and the Netherlands experienced important improvements in output and investment in the 1990s compared to the 1980s, however the labour and total factor productivity slowed down in the second half of the 1990s. These trends are shown in Figure 1, which presents the evolution of GDP per hour in the United States from 1985 to 2001 relative to the four European countries considered in this paper (EU-4). The year 1995 is a clear break point in our series and it shows the deteriorating performance of the European countries compared to the US.

Figure 1

Labour productivity (Real GDP per hour) in the EU-4 relative to the US, 1985-2002. (US=100)



Source: Groningen Growth and Development Centre and The Conference Board, Total Economy Database, 2004 (http;//www.ggdc.net)

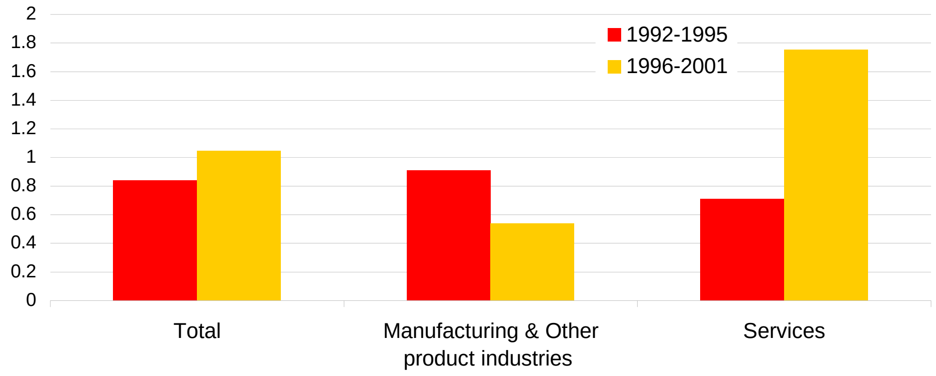
The literature to date has emphasised the importance of service sectors in driving US productivity growth (Triplett and Bosworth 2003) and the poor relative performance of Europe in these sectors (O'Mahony and van Ark 2003). Similar patterns of productivity growth can be observed in the company data. By splitting the data into manufacturing and services we can also compare the performance of these two broad sectors. Using 1995 as the break point, we compare labour productivity movements in 1992-1995 and 1996-2001. Starting with the US (Figure 2) labour productivity growth in the total company sample has experienced an increase in the period 1996-2001, compared to the previous 5 years[1]. This is the result of rapid growth in the service sector, that has more than compensated the slowdown that occurred in the production sector (manufacturing and other production industries combined). The productivity acceleration in services has been noticeable, growing from 0.71% in the period 1992-1995 to

[1] Note that the aggregate economy results are based on weighted average growth rates, since the sample was not considered representative of the actual industry structure. The weights were calculated for each country using the average shares of manufacturing, other production industries and services in total GDP over the period 1990-2001.

1.75% in the last 6 years of the sample, while the production industries have suffered a decline from 0.82% growth to 0.54% growth towards the end of the period[2].

Figure 2

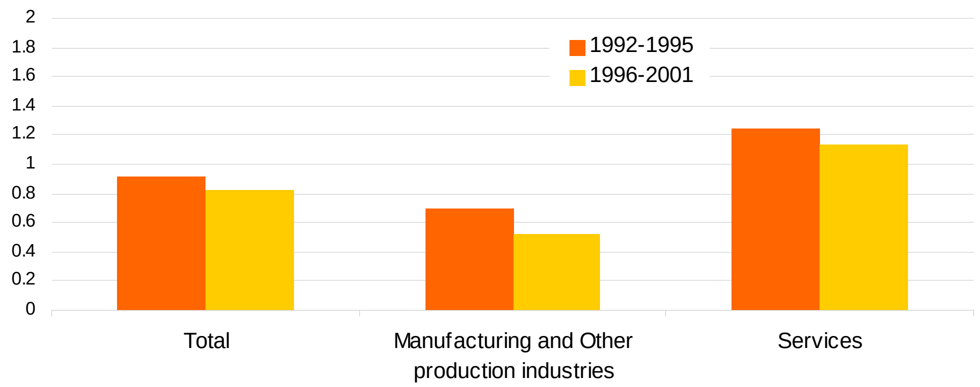
The evolution of average labour productivity growth in the US (%)



Among the EU-4, labour productivity growth decreased from a weighted average rate of 0.94% in the period 1992-1995 to 0.71% in the period 1996-2001 (Figure 3). Contrary to the US, both manufacturing and service sectors suffered a reduction in labour productivity performance across the two periods. In the production sector, the rate of growth of productivity decreased from 0.77% to 0.47% and in services from 1.20% to 1%.

Figure 3

The evolution of average labour productivity growth in the EU-4 (%)



[2] Note that the weighted averages for the two sub-periods are not based on equal number of observations. The sub-period 1992-1995 comprises one year less than the sub-period 1996-2001 and during the first period far less companies report data.

Different explanations have been put forward to understand the weaker productivity performance of the EU countries compared to the US. One that has been emphasised in the recent literature is the impact of ICT in raising growth and the possibility of a lagged response in Europe; this is the subject of the remainder of the paper.

2. ICT AS A GENERAL PURPOSE TECHNOLOGY AND A SOURCE OF SPILLOVERS

Analysing the impact of ICT capital on productivity performance has been a considerable part of economic research on productivity in the last few years. This is hardly surprising given the pervasiveness of this new technology. Computers have not just changed the way production works but many day-to-day activities have been transformed by the 'ICT revolution'. The massive reduction in computing and communications costs has triggered a substantial restructuring of the economy, (Brynjolfsson and Hitt 2000), leading to potential productivity gains.

The widespread applications of ICT has contributed to its classifications as a General Purpose Technology (GPT) that, like other GPTs in the past[3], is characterised by pervasiveness, technological dynamism and innovational complementarities (Bresnahan and Trajtenberg 1995). Pervasiveness means that a GPT is used as a component input in many downstream sectors because it provides a generic function. Technological dynamism results from the GPT's ability to support continuous innovation and learning, and innovation complementarities exist because of mutually reinforcing productivity gains generated by the GPT for it downstream applications and vice-versa. These technological complementarities, that we refer to as spillover effects, are created by the evolution of GPT and all the investments that it generates. The implementation of new processes, procedures or organisational structures, magnify the effects of innovation in the GPT, and help them propagate through the economy. In particular, these investments lead to productivity increases by enabling firms to reduce costs and increase output quality in the form of new products or intangible aspects of existing products such as convenience, timeliness, quality and variety. (Brynjolfsson and Hitt 2000). The complementary integration of these technological elements imply the existence of strong static and dynamic spillovers (Lipsey *et al.* 2003).

Spillovers have long been recognised as important components of the social benefits of technical advances and the analysis of spillovers has generated a wide interest, particularly in relation to investments in R&D (see, for example, Griliches 1992, Jones and Williams 1998).

[3] Other examples include the steam engine and electricity (Bresnahan and Trajtemberg 1995).

Investments in R&D are considered as knowledge generating activities and given that knowledge cannot be perfectly patented or kept secret its impact is not bounded within the firm that undertakes such investments but it can spread among firms, industries and countries (Romer 1990)[4]. Knowledge can spread even more easily when computers are involved. The use of the Internet, for example, has made a vast amount of information accessible to both producers and consumers, and therefore the accumulation of this type of capital can be more directly related to spillovers when compared to the more general R&D capital.

As a GPT, ICT reconciles several explanations of knowledge spillovers. For example the re-organisation of the production process within firms can be considered the result of a learning by doing process: the more we invest in ICT, the more we learn about their potential applications which makes it possible to re-organise production in a more efficient way. ICT is also a source of 'pecuniary spillovers' (Griliches 1990)[5] as the combination of innovation in the ICT producing sector and competition has allowed computer-using industries to benefit from lower costs. This source of spillover from the upstream to the downstream sector is also referred to as *vertical externality* (Bresnahan 1986). Next to this vertical externality we can also identify a horizontal one, related to the sharing of the GPT among a large number of sectors. This links 'the interests of players in different application sectors, and is an immediate consequence of generality of purpose' (Bresnahan and Trajtemberg 1995).

Another source of spillovers is the increased efficiency of transactions among firms using ICT technology. Rowlatt (2001) and Criscuolo and Waldron (2003) argue that the use of Electronic Data Interchange (EDI), internet-based procurement systems and other inter-organisational information systems produce a reduction in administrative costs, search costs, and better supply chain management. Atrostic and Nguyen (2004) find evidence for US manufacturing of this ‘network externality’, that arises when the efficiency of products or services increases as products or services are adopted by more users. Brynjolfsson and Hitt (2002) present some case studies showing how ICT makes it possible for firms to interact with others in a faster and more efficient way. Electronic transfer of payment and invoices, automated inventory replenishment, on-line markets for placing and receiving orders have all improved efficiency and consumers have benefited from increasing product variety and convenience.

[4] O'Mahony and Vecchi (2002) also provides evidence of the impact of R&D spillovers on firms that do not undertake any R&D investment.
[5] Griliches (1990) does not consider this type of spillovers as proper knowledge spillover as they are mainly the result of an incorrect measure of capital equipment, materials and their prices.

Several firm-level studies find that spillovers from ICT capital exist (Brynjolfsson and Kemerer 1996). Brynjolfsson and Hitt (2000) analyse the contribution of computer spending to productivity growth at the firm level in the US, using a large sample of 600 firms for the period 1987-1994. They find evidence of a substantial relationship between computers and multi-factor productivity growth, and that these contributions rise significantly in the long-term because computers complement productivity-enhancing organisational changes carried out over a period of years.

Using firm-level data, Van Leeuwen and van der Wiel (2003) analyse the extent to which ICT spillovers matter to the TFP growth of firms in service sector in the Netherlands, including ICT capital stocks at the industry level in the econometric specification. They find that controlling for ICT spillovers lowers elasticities of ICT capital, suggesting that ICT spillovers can be an important source of TFP growth in ICT-using industries.

How does all of the above relate to the upsurge in productivity growth in the US in the second half of the 1990s and the slowdown in Europe in the same period? One possible answer to this question is that the benefits of GPT may not be realised in the short term, since the materialisation of complementary investments and reorganisation of productive processes will require several years before they are maximised. Helpman and Trajtenberg (1998) describe the diffusion of GPT as two-phase cycle. '*The first phase is the "time to sow", in that resources are diverted to the development of complementary inputs that would allow to take advantage of the new GPT. During this initial stage output and productivity experience negative growth, and the real wage stagnates. The "time to reap" comes in the second phase after enough complementary inputs have been developed , making worthwhile to switch to manufacturing to the new, more productive GPT. As a consequence there is a spell of growth, with rising output, real wages and profits. '.* If Europe is still in the 'time to sow' period it might take few more years for the positive impact of ICT to show up in the productivity statistics.

Basu *et al.* (2003) find that a large part of the strong measured US TFP acceleration of the late 1990s can be attributed to the use of ICT and the role of complementary investments or innovations induced by it; this is consistent with the predictions of models of ICT as a General Purpose Technology. Initially ICT investments are found to be negatively correlated with output and positively correlated with complementary investments. Only after the investments have taken place and the stock of complementary investments is high, does measured productivity growth increase. They estimate that ICT capital growth is associated with TFP growth with long and variable lags of 5 to 15 years. They compare the experience in the US with the UK, where labour and total factor productivity decelerated in the second half of the 1990s, performing similarly to the rest of Europe. In the UK the rapid growth of ICT investments after 1995 did not have an impact on measured productivity growth, and the fact that during that period UK firms were accumulating complementary capital intensively, suggests that the UK could see an acceleration in TFP growth over the next decade.

3. DATA AND METHODOLOGY

3.1 Company accounts data

The company accounts database employed in the analysis, Compustat, includes financial and market data on more than 13,000 international companies in more than 80 countries. The dataset covers all sectors of the private market economy except agriculture, private health and education sectors. From this we have extracted information for the United States, and the four European countries (EU-4) for the time period 1991-2001.. The primary data series extracted from the company accounts were net sales, employment, net physical capital, defined as equipment and structures (PPE) and R&D expenditures. Net sales were deflated using industry specific price indices for each country and then converted to US $ using the market exchange rate. Net physical capital at historic cost was converted into capital at replacement costs (Arellano and Bond 1991). Our attention to R&D expenditure is justified by the existing evidence that ICT and R&D are complementary investments (Bresnahan and Trajtenberg 1995, Motohashi 2001) and they should therefore be analysed within the same framework. R&D expenditure was converted into a stock measure using a perpetual inventory method, together with the assumption of a pre-sample growth rate of 5% and a depreciation rate of 15% (see Hall 1990 for details).

Companies that did not disclose any data for net sales, employment or net physical capital were dropped, as were those companies displaying negative values. We also dropped companies for which the growth rate of these variables was more than 150% or lower than –150[6]. The number of these companies was not very high but their inclusion did affect the computation of labour productivity growth rates and our coefficient estimates.

The Compustat Database classifies companies to industries according to the 1987 US Standard Industrial Classification (SIC). Companies are sampled from a wide range of industrial sectors, both manufacturing and the service sectors. The inclusion of the service sector is particularly important for our analysis not only because it accounts for a large share of the

[6] This criterion to remove outliers has been used recently in Aghion *et al.* (2002) and Bloom and Van Reenen (2000).

economy in all countries, but also because this sector has invested heavily in ICT capital. There is evidence that these investments have produced particularly high productivity advantages in the service sector (Inklaar *et al.* 2003).

Appendix table A.1 presents the distribution of the companies included in the analysis across industries and countries. The total sample for the US and the EU-4 countries are of very similar magnitude. However there is a different distribution of companies performing R&D in manufacturing and other production industries. In the US over 60% of the companies report R&D investments, while in the EU-4 countries around 40% of the companies do not disclose any information on R&D. Looking across sectors a larger number of R&D companies can be found in manufacturing in all countries. In our analysis we assume that non R&D reporting companies are those that have not invested in R&D for more than two consecutive years. Data on R&D are particularly poor in each single country. For example, in the Netherlands, only 19 companies within manufacturing and other production industries and 8 in services have invested in R&D. This precludes a country by country analysis, and is the basis of our decision to analyse the four European countries jointly.

Appendix table A.2 presents some descriptive statistics on employment, physical capital stock, R&D capital stock and sales for the EU-4 and US. In terms of the number of employees, capital and turnover, US firms are on average the largest. US companies are also more capital intensive, as can be seen from the capital to labour ratio. EU-4 companies are characterised on average by higher sales to employment ratio than the US.

3.2. Modelling the impact of ICT spillovers on productivity

The starting point of our analysis is a log linear (Cobb-Douglas) production function[7] where output (Y_{it}) is expressed as a function of capital (K_{it}), labour (L_{it}) and R&D capital (R_{it}). Letting lower case letters denote the log of a variable, this can be written as:

$$y_{it} = a_i + \alpha k_{it} + \beta l_{it} + \gamma r_{it} + \varepsilon_{it} \ , \qquad (1)$$

where a_i is a company specific intercept (fixed effect).

Taking first differences, we can re-write equation (1) as follows:

$$\Delta y_{it} = \alpha \Delta k_{it} + \beta \Delta l_{it} + \gamma \Delta r_{it} + \Delta \varepsilon_{it} . \qquad (2)$$

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[7] The use of other function forms, such as the CES or the translog function, has sometimes been suggested. However, these alternative formulations do not seem to provide substantial improvements to the estimates (Griliches and Mairesse 1984).

In equation (2) we express the change in productivity as a function of the change in the factor inputs. Company account data do not provide information on firm specific ICT investment but it is included in total capital. So although we cannot separately evaluate the impact of ICT and non-ICT capital, the presence of ICT capital is accounted for.

The impact of ICT spillovers can be measured by introducing ICT capital at a higher level of aggregation than the original data. As in van Leeuwen and van der Wiel (2003), we try to capture learning by doing effects associated with the increase in aggregate ICT capital stocks. Measuring spillovers by introducing an index of aggregate activity is a method that has been widely used in the existing literature (Caballero and Lyons 1989, 1990, Vecchi 2000). Both aggregate output and aggregate input have acted as proxies for spillovers (Oulton 1996). One drawback of this methodology is that the aggregate variable is likely to pick up unmeasured input variation over the cycle. Also since the externality index is the same for several companies in a given year, it may be functioning simply as a proxy for a set of time period dummies. The latter in turn could be interpreted in a large number of different ways, without necessarily any role for externalities (Oulton 1996). To address this issue, we introduce time dummies in all estimations. Therefore, any spillover effect will be net of other cyclical and/or exogenous components.

In order to consider how different measures of spillovers impact on productivity we use two aggregate measures of ICT. First we use ICT at the industry level under the assumption that the productivity of a single company is affected by the investment in ICT in its own industry. For example, it is not unreasonable to think that the output of a pharmaceutical company is affected by the ICT undertaken in the whole chemical industry. Aggregate ICT at the industry level can only account for spillovers within the industry (vertical spillovers) but cannot say anything about the presence of spillover across different industries (horizontal spillovers). We therefore construct a wider ICT aggregate by combining industry ICT according to a taxonomy developed in van Ark *et al.* (2002). This taxonomy groups industries based on whether they produce ICT or use ICT more or less intensively. A list of the sectors included in each group is reported in Appendix table A.3. This measure aims at capturing spillover effects across companies operating in different industries but sharing a common ICT adoption pattern. Both measures of aggregate ICT are weighted by the number of employees, to account for the impact of industry/sector size.

For Europe we also investigate whether ICT investments in the US impact on the productivity of European companies. Given that the US has acted as the leader in the introduction of ICT we expect that part of the knowledge will spill across the borders and affect the productivity of 'follower' countries.

Expanding equation (2) to include aggregate ICT (S) we obtain the following:

$$\Delta y_{it} = \alpha \Delta k_{it} + \beta \Delta l_{it} + \gamma \Delta r_{it} + \delta \Delta S_{\tau} + \Delta \varepsilon_{it} \qquad (3)$$

$$\tau = 1,..,3,$$

where $\tau = 1,..,3$ refers to industry ICT, sector ICT and US ICT.

The industry data used to proxy the spillover effect covers the entire non-agricultural market economy in the five countries in our study. ICT capital is measured using Törnqvist capital services indices comprising three asset categories within ICT capital (computers, software and communications equipment). Capital stocks were estimated for each asset using the perpetual inventory method, assuming exponential depreciation with rates that vary across industries but are assumed common in the same industry in the different 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 based on user costs of capital. US deflators for ICT assets, in particular the computer hedonic price index, adjusted for exchange rate movements, were employed for all countries (See O'Mahony and van Ark 2003 for more details)[8].

3.3 Short run versus long run spillover effects.

The second issue we consider is the possibility of a lagged impact of ICT on productivity. As argued above, it may take some time for ICT to impact on production because of the complementary investments involved in the implementation of this technology. The lags might be even longer for the generation of spillover effects.

In panel data analysis the first difference specification used in the previous section is generally considered equivalent to the fixed effect estimator as they both account for the heterogeneity in the data (Baltagi 1995). For T = 2 the two techniques produce identical results (Wooldridge 2002). However, when the time dimension increases the two specifications can have different implications, that is they imply different assumptions as to the time series behaviour of our data. If the series are non stationary the fixed effect estimates can produce

[8] The classification, developed for the US, is used to combine the industry data in all the countries included in this study. This should not cause any problem in the empirical analysis because given the leading role of the US it is reasonable to assume that the distribution of ICT use in the US represents a set of technological opportunities which may have been taken up in other countries. Indeed, van Ark *et al.* (2002) show that the ranking of ICT intensity across industries is fairly similar in the US and the EU. A list of the sectors included in each group is given in Appendix table A.3.

highly misleading results. On the other hand, if the series are of the same order of integration and are cointegrated, the first difference and the level (fixed effect) specifications can be used to infer about the short-run and the long run impact of the right hand side variables.

Recently a growing literature has concentrated on the time dimension of panel data and various techniques have been developed in order to account for it. For example, unit root tests for panel data have now become a standard way to proceed to test for the stationarity of a panel, as well as to test whether the variables used in our relationship are cointegrated. If this is the case, a different interpretation can be given to the fixed effect version of equation (3) and comparing the estimates of the first difference and fixed effect model can tell us about the short and the long run impacts of the inputs and the spillover effect on productivity. We therefore re-write equation (3) as follows:

$$y_{it} = a_i + \alpha k_{it} + \beta l_{it} + \gamma r_{it} + \delta s_{\tau} + \mu_{it} \qquad (4)$$

In order to estimate consistent long-run coefficients, we first need to check for the presence of unit roots in our data. If the assumption of a unit root cannot be rejected, we can test whether there exists a linear combination of our variables, as in equation (4) above, which is stationary, i.e. the residuals do not contain a unit root. If this is the case, our variables are cointegrated and we can consistently estimate the long-run production function parameters[9].

4. EMPIRICAL EVIDENCE ON ICT PRODUCTIVITY SPILLOVERS

4.1 ICT spillovers in the short run

We start our empirical investigation with the estimation of a production function including R&D capital, as in equation (2). Apart from measurement errors and omitted variables, one of the problems with the estimation of a production function is the possible endogeneity of the right hand side variables. The usual solution is to use an instrumental variable techniques but the lack of good instruments can cause more problems than endogeneity itself (Bound *et al.* 1993). For this reason we present in this section both OLS and GMM results and discuss their implications.

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[9] Ideally, if the variables are cointegrated, we could estimate an error correction model where the short-term dynamics of the variables are influenced by the deviation from equilibrium. However, the highly unbalanced nature of our data set prevent us to do so without the loss of a large number of observations, particularly for the European countries.

Table (1) presents the results for the US. Column (1) presents the estimation of a standard production function with R&D capital. The OLS results are consistent with our *a priori* expectations about coefficient size and significance, based on knowledge of factor shares. The size of the R&D coefficient (0.157) is consistent with existing evidence for the US economy. For example, Griliches, in two successive papers, finds that, in United States manufacturing, the elasticity of output to R&D is around 0.07 on average, ranging between 0.1 for the research intensive sector and 0.04 for the rest of the manufacturing industries (Griliches 1979, 1984). Schankerman (1981) and Griliches and Mairesse (1984) present estimates of the output elasticity to R&D for the US which rise to about 0.18.

The GMM results, presented in columns (5)-(8), give more weight to both capital and R&D compared to the OLS. In column (4) however, capital becomes insignificant. Overall, the OLS results suggest the presence of slightly decreasing returns to scale while the GMM results suggest constant returns.

The coefficients on the inputs are quite robust to the introduction of our first measure of spillovers, i.e. the rate of growth of ICT/N at the industry level. In all cases we find a positive spillover effect, albeit quite small. A 1% increase in aggregate ICT leads to a 0.7% increase in companies' productivity. In column (3) we drop R&D from the specification of the production function and this results in a higher spillover coefficient (0.009 as opposed to 0.007 when R&D is included). This provides evidence of the complementarity between R&D and ICT and the importance of including both types of capital in the specification, in order to get a more precise estimate of the spillover effect. On the other hand, when we looked at the companies that do not invest in R&D (results not shown) the spillover effects become much smaller. This suggests that companies that invest in knowledge generating activities are more able to take advantage of the pool of ICT capital within the industry and to reap the benefit of ICT spillovers (O'Mahony and Vecchi 2002)[10].

A positive ICT spillover effect can also be found when using the wider ICT aggregate, ICT sect. Given the *generality of purpose* of ICT (Bresnahan and Trajtemberg 1995) we do expect spillovers across different sectors (horizontal externalities), even though in our specific case the impact is weaker than the within industry effect. Similar results for the spillover effect are obtained in OLS and GMM.

[10] When estimating specification (3) for non-R&D companies, the spillover effect dropped to 0.003. Results are available from the authors on request.

Table 1: United States

First difference production function estimates

	OLS (1)	OLS (2)	OLS (3)	OLS (4)	GMM (5)	GMM (6)	GMM (7)	GMM (8)
L	0.530	0.531	0.549	0.530	0.462	0.491	0.443	0.751
	(.023)	(.023)	(.022)	(.023)	(.097)	(4.16)	(.085)	(.123)
K	0.167	0.167	0.191	0.166	0.326	0.314	0.467	0.129
	(.017)	(.017)	(.017)	(.017)	(.065)	(3.83)	(.127)	(.085)
R&D	0.157	0.150		0.135	0.238	0.181		0.257
	(.025)	(.025)		(.024)	(.094)	(2.40)		(.117)
ICT ind		0.007	0.009			0.007	0.007	
		(.002)	(.002)			(2.32)	(.003)	
ICTsec				0.005				0.002
				(.001)				(.001)
Sargan					231.8	108.8	158.2	106.0
					(.000)	(.003)	(.000)	(.000)
AR(1)	-1.874	-1.998	-1.861	-2.107	-1.978	-2.395	-2.561	-3.437
	(.061)	(0.046)	(.063)	(.035)	(.048)	(.017)	(.010)	(.001)
AR(2)	-1.708	-1.842	-1.393	-2.003	-2.352	-2.368	-2.515	-1.720
	(0.088)	(0.065)	(.164)	(.045)	(.019)	(.018)	(.012)	(.085)

Notes: Standard errors in brackets. ICTind is ICT/N at the two-digit industry level. ICTsec aggregates the two-digit industry ICT/N according to the ICT using/producing taxonomy (van Ark *et al.* 2002).

One source of concern with the GMM technique is that in all estimations the Sargan test rejects the validity of the instruments. There is evidence that this test tends to over-reject the null hypothesis in equations specified in first difference (Blundell and Bond 1998). Table 1 also shows first order (AR(1)) and second order (AR(2)) serial correlation tests of the first differenced residuals. In order to obtain consistent GMM estimates the assumption of no serial correlation in the residual in levels is essential. This assumption holds if there is evidence of significant and negative first order serial correlation and no evidence of second order serial correlation in the first differenced residual (Arellano and Bond 1991). Our results however do show the presence of both first order and second order serial correlation – the only exception being column (3) and this again suggests that we have some problems with our GMM instrument sets.

In Europe (Table 2) the estimation of the coefficients of the factor inputs suggests decreasing returns to scale in most specification, with the exception of columns (9) and (10) which show increasing returns. The capital coefficient is slightly lower that expected in the OLS estimates while the GMM seems to correct for that. However, R&D capital, which is high and significant in the OLS specification, becomes insignificant and even negative in the GMM estimates.

As for the spillover effect this appears to be significant only among those companies that do not invest in R&D as in column (8). This is quite surprising as one of our assumptions is that performing R&D increases the absorptive capacity towards spillovers. Note, however, that again the Sargan test rejects the null hypothesis of the validity of our instruments and therefore our coefficient estimates are likely to be biased.

The lack of a spillover effect in Europe is consistent with the later adoption of ICT compared to the US. Despite the catching up in ICT diffusion in Europe, the existing evidence so far shows that there have been very few productivity gains (Daveri 2002). Consequently, spillover effects might take even more time to produce the desired positive effect on productivity.

Finally, our results show that although the OLS estimates might be affected by endogeneity, they are in this context preferred to the GMM estimates because of the poor quality of our instruments and the lack of robustness of the GMM results. If the assumed properties of the instruments are not met, i.e. no correlation with the error term and high correlation with the endogenous variable to be instrumented, the cure may be worse than the disease (Oulton 1996). Bound *et al.* (1993) argue that if the instruments are only weakly correlated with the endogenous variables they can lead to a large inconsistency in IV estimates. The *internal* instruments used in the GMM estimator are likely to be quite poor (Griliches and Mairesse 1995) because of the very low correlation with the variables they are meant to instrument, caused by the highly persistent nature of the data[11]. If two random variables , x and z, were strictly random walks, there would be no power at all in their past levels as instruments for their current differences (see also stationarity tests in the next session)[12].

[11] The weak correlation issue is also discussed in Biscourp *et al.* (2002).

[12] Blundell and Bond (1998) show for first-differences GMM estimators that weak instruments may result in finite sample biases when using persistent series such as firm sales, capital and/or employment. They find that GMM-System estimator reduces these finite-sample biases associated with first-differenced GMM by using valid and informative additional instruments (Arellano and Bover 1995). However, even when using the system GMM in our case we could no get robust results.

The coefficients on the ICT spillover terms are, however, largely unaffected by the estimation method used, OLS or GMM. Therefore, the analysis in the reminder of the paper will be based on OLS.

Table 2: Europe

First difference production function estimates

	OLS (1)	OLS (2)	OLS (3)	OLS (4)	OLS (5)	GMM (6)	GMM (7)	GMM (8)	GMM (9)	GMM (10)
L	0.618	0.617	0.514	0.616	0.619	0.516	0.529	0.679	0.870	0.768
	(.039)	(.039)	(.021)	(.039)	(.039)	(.156)	(.135)	(.118)	(.131)	(.127)
K	0.137	0.138	0.141	0.138	0.136	0.324	0.254	0.215	0.196	0.228
	(.002)	(.027)	(.014)	(.027)	(.028)	(.102)	(.085)	(.105)	(.099)	(.085)
R&D	0.129	0.130		0.121	0.130	0.112	0.168		-0.263	-0.042
	(.046)	(.046)		(.046)	(.046)	(.176)	(.145)		(.181)	(.185)
ICT ind		0.002	0.004				0.002	-0.003		
		(.002)	(.003)				(.003)	(.003)		
ICTsect				0.003					0.005	
				(0.002)					(.003)	
ICTus					0.003					-0.001
					(.002)					(.002)
Sargan						47.93	112.7	84.36	82.67	75.57
						(.245)	(.009)	(.101)	(.012)	(.067)
AR(1)	-1.089	-1.085	-3.622	-1.162	-1.095	-2.012	-1.718	-1.084	-0.789	-1.606
	(.076)	(.278)	(.000)	(.245)	(.273)	(.044)	(.086)	(.278)	(.424)	(.108)
AR(2)	-2.689	-2.711	1.495	-2.723	-2.742	-2.527	-2.609	-2.236	-2.144	-2.459
	(.007)	(.007)	(.135)	(.006)	(.006)	(.011)	(.009)	(.025)	(.032)	(.014)

Notes: Standard errors in brackets. ICTind is ICT/N at the two-digit industry level. ICTsec aggregates the two-digit industry ICT/N according to the ICT using/producing taxonomy (van Ark et al. 2002). ICTus is the ICTsec for the US.

4.2 ICT spillovers in the long run

The investigation of a long run spillover effect starts with the analysis of the time series properties of our data. We first check the stationarity of our data by applying a test developed by Hadri (2000). This is a residual based Lagrange multiplier test for the null that the individual observed series are stationary against the alternative of unit root in panel data. The results are presented in table 3 below. 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 strong evidence of the presence of unit roots in our data.

Table 3

Test of the null hypothesis of stationarity

	Hadri(1)	Hadri(2)	Hadri(3)
United States			
Output	76.168 (.000)	62.256 (.000)	42.871 (.000)
Employment	71.723 (.000)	56.870 (.000)	40.653 (.000)
Capital	71.595 (.000)	57.397 (.000)	40.233 (.000)
R&D	83.696 (.000)	73.451 (.000)	46.498 (.000)
ICTind	24.202 (.000)	16.356 (.000)	75.498 (.000)
ICT sect	6.189 (.000)	6.613 (.000)	3.744 (.000)
Europe			
Output	35.279 (.000)	27.349 (.000)	20.239 (.000)
Employment	29.987 (.000)	23.806 (.000)	17.169 (.000)
Capital	25.936 (.000)	18.861 (.000)	15.084 (.000)
R&D	40.576 (.000)	36.558 (.000)	22.259 (.000)
ICTind	39.016 (.000)	30.770 (.000)	171.916 (.000)
ICTsect	11.408 (.000)	11.282 (.000)	11.584 (.000)

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

Given that all our variables are I(1) we can use cointegration techniques to test for the presence of a long-run relationship, as described by equation (4). The tests for cointegration are from Pedroni (1999). Pedroni develops seven cointegration tests for panel data, four are *within model* and three are *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. The latter, also called group mean panel cointegration statistics, are based on estimators that simply average the individually estimated coefficients for each member *i*. The tests allow for considerable heterogeneity among individual members of the panel, including heterogeneity in both the long run cointegrating vectors and in the dynamics associated with short run deviations from these cointegrating vectors. The null hypothesis is that the variables of interest are not cointegrated for each member of the panel. The alternative hypothesis is that there exists a single cointegrating vector for each member of the panel, although this cointegrating vector need not be the same for each member.

To construct the tests we compute the regression residuals from the hypothesised cointegrating regression (Equation 4 above). We allow for the presence of common time effects by demeaning the data over the cross section dimension. This procedure is equivalent to adding time dummies to the regression, when the slope coefficients are homogeneous and/or the sample is quite large in the cross section dimension.

Conventional cointegration tests would suffer from unacceptably low power in our application, given the moderate length of our series (11 years at most). However, by pooling data across individual members of a panel this issue is addressed by making available considerably more information regarding the cointegration hypothesis.

We present the results for four of the Pedroni (1999) tests, two for the panel cointegrating statistic and two for the group cointegrating statistics, as in Sarantis and Stewarat (2001) and O'Mahony and Vecchi (2004)[13]. Each test is distributed as a standard normal variable, $\longrightarrow N(0{,}1)$, The results for the US and Europe are presented in table 4. The null of no cointegration is rejected by all the tests in table 4. This suggests that we can consistently estimate a long run relationship.

Table 4

Pedroni Panel cointegration tests[14]

	ICT ind	ICT sect	US ICT sect
US Results			
Panel pp	-39.739*	-39.420*	
Panel adf	-22.441*	-19.638*	
Group pp	-59.262*	-58.833*	
Group adf	-16.270*	-15.657*	
Europe Results			
Panel pp	-14.643*	-15.235*	-12.591*
Panel adf	-6.597*	-6.947*	-6.777*
Group pp	-20.928*	-24.968*	-22.609*
Group adf	-4.076*	-2.783*	-5.012*

Notes: 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. Results are based on cross-sectionally de-meaned data.

[13] The between dimension (Group pp and Group adf) estimators have the advantage of allowing for greater flexibility in the presence of heterogeneity of the cointegrating vectors. Also Pedroni (2000) shows that they appear to suffer from much lower small sample size distortion than the within-dimension estimators (Pedroni 2001). Table 4 also presents two versions of the Panel tests for comparison purposes.

[14] The tests are based on an unbalanced sample of 10 and 11 observations. This in order to allow more dynamics in the estimation of the statistics presented in table 4.

The results from the estimation of equation (4) are presented in table 5 and 6 for the US and Europe respectively. We also extend our investigation to look at possible differences in the manufacturing and service sectors. For the US the coefficient estimates of the factor inputs are all consistent with *a priori* knowledge of revenue shares, with a higher labour coefficient in the service sector than in manufacturing and a slightly higher capital coefficient in manufacturing. Also the returns to R&D are consistent with previous studies (Griliches 1979, 1984, Griliches and Mairesse 1984). Overall, the results suggest constant *interna*l returns; however the returns are slightly decreasing in the manufacturing sector, while they are not significantly different from 1 in the service sector[15].

The spillover effect is similar to the one depicted in the short run specification, with a higher short run coefficient for the ICT industry aggregate, estimated for all companies (0.7% in the short run as opposed to 1.5% in the long run). This shows that although the technology is well established in this country there is still some scope for extra productivity gains from an increase in the overall stock of ICT capital. When we look at manufacturing *versus* services we find significantly larger spillovers in the former. A 1% increase in ICT at the two-digit industry level leads to a 2.5% increase in companies' productivity performance. The impact is smaller when we look at the wider ICT aggregate (ICTsect), but we still get a positive and significant spillover effect (1.2%) In services the larger ICT aggregate is not significantly different from zero, suggesting that vertical rather than horizontal spillovers are more important in the service sector.

[15] We test the null hypothesis that the sum of labour, capital and R&D coefficients equals 1. For manufacturing, the probability value is 0.008 in the specification with ICT ind and 0.000 in the specification with ICT sect. For services the probability values are 0.102 and 0.140 respectively.

Table 5

US Long run estimates

(Fixed effect estimator)

	All sectors		Manufacturing		Services	
US Results						
L	0.659*	0.651*	0.663 *	0.669*	0.712*	0.711
	(.012)	(.011)	(.013)	(.013)	(.024)	(.024)
K`	0.188*	0.192*	0.186 *	0.180 *	0.183 *	0.183
	(.009)	(.009)	(.011)	(.010)	(.018)	(.018)
R&D	0.107*	0.087*	0.102 *	0.083 *	0.079 *	0.082
	(.010)	(.010)	(.012)	(.011)	(.021)	(.021)
ICT ind	0.015*		0.024 *		0.004 *	
	(.001)		(.001)		(.002)	
ICTsect		0.007*		0.012 *		-0.001
		(.000)		(.000)		(.001)

Notes: Standard errors in brackets. ICTind is ICT/N at the two-digit industry level. ICTsec aggregates the two-digit industry ICT/N according to the ICT using/producing taxonomy (van Ark et al. 2002).

Table 6 presents the long run coefficient estimates for Europe. The results for all companies show a higher capital elasticity and a lower labour elasticity, compared to the short-run estimates presented in table 4. The estimates of the R&D coefficient, although smaller in the long run, are not significantly different from the short run results. The difference between the manufacturing and the service sector is more pronounced in Europe than in the US. The coefficient estimates for labour and capital are consistent with existing growth accounting estimates, with service sector companies being characterised by higher labour elasticity and lower capital elasticity. More surprising is the difference between the R&D coefficients in the two sectors. Our results show that there are higher R&D elasticities in services than in manufacturing, consistent with O'Mahony and Vecchi (2002). This suggest that R&D investments are also particularly important in fostering productivity performance outside of the manufacturing sector. The hypothesis of constant returns to scale is rejected at the 5% significance level in all specifications. Our results suggest internal returns of around 0.8.

Table 6

Europe Long run estimates

(Fixed effect estimator)

	All sectors			Manufacturing			Services		
L	0.303*	0.300*	0.301*	0.233*	0.235*	0.240*	0.591*	0.591*	0.586*
	(.014)	(.014)	(.014)	(.016)	(.015)	(.015)	(.036)	(.036)	(.036)
K	0.417*	0.424*	0.416*	0.460*	0.465*	0.457*	0.239*	0.241*	0.240*
	(.015)	(.015)	(.015)	(.017)	(.017)	(.017)	(.029)	(.029)	(.029)
R&D	0.113*	0.093*	0.093*	0.089*	0.074*	0.076*	0.124*	0.114*	0.108*
	(.012)	(.012)	(.012)	(.013)	(.013)	(.014)	(.028)	(.029)	(.029)
ICT ind	0.006*			0.006*			0.001		
	(.002)			(.002)			(.002)		
ICTsect		0.007*			0.008*			.001	
		(.001)			(.001)			(.001)	
ICT US			0.007*			0.007*			0.003*
			(.001)			(.001)			(.001)

Notes: Standard errors in brackets. ICTind is ICT/N at the two-digit industry level. ICTsec aggregates the two-digit industry ICT/N according to the ICT using/producing taxonomy (van Ark et al. 2002). ICTus is the ICTsec for the US.

The main difference between the short and the long run coefficient estimates, however, is that we now find a positive and significant evidence of ICT spillovers in Europe. The results are particularly significant in the manufacturing sector, where all the different aggregates are positive and significant. A 1% increase in aggregate ICT produces an approximately 0.7% increase in companies' productivity. In services the spillover effect is not significantly different from zero when using internal ICT capital while we obtain a positive and significant impact from US ICT capital, i.e. there is evidence of cross-country spillovers. In the US, ICT at the industry level has a stronger impact on productivity compared to the wider ICT aggregate, the former being approximately twice as large as the latter. In Europe, on the other hand, the wider ICT aggregate and the ICT capital in the US appear to affect productivity more than the own industry ICT, suggesting that horizontal externalities are stronger in Europe.

5. CONCLUSIONS

This paper started with an overview of productivity performance at the company level in the US and Europe, and investigated whether the difference between the two countries can be attributed to the different timing in the implementation of ICT technology and a different impact of ICT spillovers. The results suggest that in the US both the short-run and the long-run spillover effect is positive and significant, with a larger impact in the long run, particularly in the manufacturing sector. As in previous related studies, we find evidence that Europe, being the follower country in the implementation of the new technology, might still be lagging behind the US in terms of obtaining a pay-off from investments in ICT. This is shown in the short run estimates, where the impact of ICT spillovers was not found to be significantly different from zero. However, in the long-run results, ICT spillovers are positive and significant, especially when considering the spillovers from the US.

This study, while adopting a traditional approach in measuring the spillover effect, by using a variable at a higher level of aggregation than the rest of the data, has extended the analysis in two directions. Firstly, it has considered different aggregates to evaluate the impact of spillovers, and in doing so it has attempted to get some insights into the vertical/horizontal spillover effects, as emphasised in the GPT literature (Bresnahan and Trajtenberg 1995). Our results support both of these effects in both countries. However, while in the US the vertical spillovers are stronger than the horizontal ones, in Europe we obtain the reverse.

Secondly, the paper has introduced some dynamics in the evaluation of the spillover effect. The results support the GPT implication about the timing of the impact of a new technology on productivity. Specifically they show that in the long run more can be gained by increasing the stock of ICT capital in the economy, which creates important spillover effects. In this perspective this is an innovative contribution since, as to our knowledge, this is the first attempt to consider spillovers or externalities in a more dynamic framework. Previous evidence on spillovers has mainly focused on the contemporaneous effect (Sena 2004).

This paper has tried to introduce some dynamic analysis in the traditional panel data framework but data limitations prevented a more thorough investigation. Our time dimension is at most 11 years, which precluded the use of more sophisticated dynamic analytical tools, such as for example, the Pooled Mean Group (PMG) estimator (Pesaran *et al.* 1999), where a full error correction model is estimated by imposing a common long run equilibrium and heterogeneous dynamic adjustments. Further research is needed to look more closely at the time dimension in the analysis of panel data and in the investigation of spillover effects.

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APPENDIX

Table A.1 Distribution of companies across countries and industries.

R&D companies are companies with R&D at least 3 consecutive years.

	Total	Manufacturing and other production industries[1]		Services[2]	
		R&D>0	R&D=0	R&D>0	R&D=0
US	2443	853	536	235	819
EU 4	2261	339	737	135	1069
UK	879	179	204	72	428
Germany	664	90	267	36	276
France	559	51	206	19	290
Netherlands	159	19	60	8	75

1.Includes mining and quarrying, electricity, gas & water and construction;
2.Includes transport, wholesale and retail trade, eating and drinking places and hotels, personal and amusement services, business and professional services.

Table A.2 Descriptive statistics

	Obs.	Mean	Std. Dev.	Min	Max
US					
Employment	22139	12296	40862	1	1383000
Capital	23122	1066046	3942878	7	100259000
R&D	9850	542104	2417862	17	44970710
Sales	23383	2423915	8409796	26	218227000
Capital-Employment ratio	21904	262	3975	0.07	193797
Sales-Employment ratio	22092	261	525	0.15	24268
EU-4					
Employment	15351	11379	32850	1	484000
Capital	15846	990838	4564560	1	107786700
R&D	3256	795916	2744660	14	29616120
Sales	17233	2139483	7159617	34	156786500
Capital-Employment ratio	15183	125	1424	0.06	85548
Sales-Employment ratio	15302	373	3043	1.64	175404

Table A.3 ICT taxonomy

Manufacturing and Other production industries

ICT Producing: Office machinery (30); Insulated wire (313); Electronic valves and tubes (321); Telecommunication equipment (322); Radio and television receivers (323); Scientific instruments (331).

ICT Using: Clothing (18); Printing & publishing (22); Mechanical engineering (29); Other electrical machinery & apparatus (31-313); Other instruments (33-331); Building and repairing of ships and boats (351); Aircraft and spacecraft (353); Railroad equipment and transport equipment Nec (352-359); Furniture, miscellaneous manufacturing; recycling (36-37).

Non-ICT : Food, drink & tobacco (15-16); Textiles (17); Leather and footwear (19); Wood & products of wood and cork (20); Pulp, paper & paper products (21); Mineral oil refining, coke & nuclear fuel (23); Chemicals (24); Rubber & plastics (25); Non-metallic mineral products (26); Basic metals (27); Fabricated metal products (28); Motor vehicles (34); Agriculture* (01); Forestry* (02); Fishing* (05); Mining and quarrying* (10-14); Electricity, gas and water supply* (40-41); Construction* (45)

Services

ICT Producing: Communications (64); Computer & related activities (72).

ICT Using : Wholesale trade and commission trade, except of motor vehicles and motorcycles (51); Retail trade, except of motor vehicles and motorcycles; repair of personal and household goods (52); Financial intermediation, except insurance and pension funding (65); Insurance and pension funding, except compulsory social security (66); Activities auxiliary to financial intermediation (67); Renting of machinery & equipment (71); Research & development (73); Legal, technical & advertising (741-3).

Non-ICT: Sale, maintenance and repair of motor vehicles and motorcycles; retail sale of automotive fuel (50); Hotels & catering (55); Inland transport (60); Water transport (61); Air transport (62); Supporting and auxiliary transport activities; activities of travel agencies (63); Real estate activities (70); Other business activities, Nec (749); Public administration and defence; compulsory social security (75); Education (80); Health and social work (85); Other community, social and personal services (90-93); Private households with employed persons (95); Extra-territorial organisations and bodies (99).