# ICT SPILLOVERS, ABSORPTIVE CAPACITY AND PRODUCTIVITY PERFORMANCE

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*Abstract*

We analyse the impact of ICT spillovers on productivity in the uptake of the new technology using company data for the U.S. We account for inter- and intra-industry spillovers and assess the role played by firm's absorptive capacity. Our results show that intra-industry ICT spillovers have a contemporaneous negative effect that turns positive 5 years after the initial investment. By contrast, inter-industry spillovers are important both in the short and in the long run. In the short run, companies' innovative effort is complementary to ICT spillovers, but such complementarity disappears with the more pervasive adoption and diffusion of the technology.

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## I. Introduction

Advances in the field of information and communication technologies (ICT) have driven a new technological revolution that has modified not only the ways of doing business but also the ways of performing daily household activities. Due to its widespread applications, ICT has been classified as a General Purpose Technology (GPT), exactly like electrification and other great inventions of the past (Jovanovic and Rousseau 2005). As a GPT, ICT is characterized by considerable technological progress, pervasive use in a wide range of economic sectors, as well as by the ability to boost complementary innovations and to generate spillover effects (Bresnahan and Trajtenberg, 1995, Lipsey et al. 2005). These characteristics have produced positive productivity effects throughout the economy (Jovanovic and Rousseau, 2005, O'Mahony and Vecchi 2005, Venturini, 2009). ICT is now recognised as an important determinant of productivity growth especially if coupled with investments in other intangible assets such as R&D, organizational and human capital (Brynjolfsson and Hitt 2000, 2003).

However, while the direct impact of ICT on productivity is well documented, it is still unclear whether ICT generates positive spillovers as the extant empirical evidence has been rather weak. While some studies find significant effects (van Leeuwen and van der Wiel 2003, Severgnini 2011, Venturini 2011), others reject the existence of spillovers (Stiroh 2002, Acharya and Basu 2010, Haskel and Wallis 2010, Van Reenen et al. 2010, Moshiri and Simpson 2011). This mixed set of results has lead researchers to doubt the importance of the GPT effects related to ICT (Draca et al. 2007) and has prevented, particularly within Europe, the formulation of appropriate policies aimed to facilitate the absorption and diffusion of new technologies.

The majority of studies that fail to find a positive ICT spillover effect are based on industry or economy wide data. It is therefore possible that the lack of spillovers from ICT is the result of an aggregation effect.[1] Here we use company level data to reassess the evidence on

ICT spillovers, and to understand their role in the US productivity revival of the 1990s. Our analysis of spillovers uses 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 (Caballero and Lyons 1990, 1992, Vecchi 2000). Therefore, we first evaluate whether companies' productivity performance is affected by the total stock of ICT capital within each industry. However, such *intra-industry* effect might only provide a partial assessment of the role of aggregate ICT as it does not account for the possibility of spillovers across industries. In fact, companies can benefit from the adoption of ICT by upstream and downstream industries, via, for example, improved service provisions (financial and shipping services). A central issue of this paper is to capture these additional effects by means of a weighted ICT industry variable, where the weights are represented by input-output coefficients. This methodology based on *inter-industry* intermediate transactions is not new to the analysis of R&D spillovers but it is less popular in constructing ICT spillover proxies (Mun and Nadiri 2002, Wolff 2011).

In a context where technological knowledge and business practices diffuse rapidly, the capacity to exploit new sources of productivity growth appears crucial to compete in the global market. We focus on the 1990s as we intend to look at the uptake of the digital economy, when firm heterogeneity is large and first-movers gain productivity benefits which may cumulate over time. Additionally, the US experienced an R&D boom in this period, particularly in high-tech sectors (Brown et al. 2009), and this could have complemented the adoption and diffusion of ICT. Hence, we will directly test the hypothesis of whether firms' investments in R&D contribute to productivity by facilitating the absorption of ICT spillovers, particularly in the initial breakthrough of innovation.

The GPT literature claims that ICT spurs further innovation over time in a wide range of industries, ultimately boosting TFP growth. This process takes time as the technology needs to be efficiently implemented within the production process. During this time, productivity can

temporarily decrease (Hornstein and Krusell 1996, Aghion 2002). Only at a later stage will firms enjoy the benefits of their investment efforts. Given this lagged impact of ICT on productivity, spillovers are also likely to be characterised by a lag, although this aspect has been scarcely explored in the most recent literature (Basu et al. 2004, Acharya and Basu 2010). By comparing contemporaneous as well as lagged effects we can achieve a better understanding of the relationship between ICT and productivity performance.

Our results show that ICT spillovers have played an important role in determining companies' TFP performance. Intra-industry ICT spillovers have a contemporaneous negative effect that turns positive some years after investment. By contrast, inter-industry spillovers are positive and significant both in the short and in the long run. Our estimates suggest that it takes approximately 5 years for intra-industry spillovers to positively affect productivity performance. Additionally, in the short run, companies' innovative effort is complementary to ICT spillovers, but such complementarity disappears over time, with the more pervasive adoption and diffusion of the technology.

The following section presents an overview of the existing empirical evidence on the impact of spillovers on productivity (section II), discussing the main implications of ICT as a General Purpose Technology (GPT) and as a potential source of spillovers. Section III presents the model used in the empirical analysis and describes the data sources. Our econometric findings are shown and discussed in sections IV and V. Section VI concludes the paper.

## II. ICT as a General Purpose Technology and a source of spillovers

Advances in general purpose technologies (GPT) can potentially generate important productivity spillovers, i.e. increases in productivity in addition to the contribution of capital deepening. Assessing the importance of such spillovers can provide economists and policy makers with the right measures to foster long-run growth (Bresnahan 1986). There have been

several attempts to describe possible channels through which spillovers affect productivity performance. A considerable effort has been directed over time to the analysis of R&D or knowledge spillovers (Jaffe 1986, Griffith et al. 2004, O'Mahony and Vecchi 2009) and a similar analytical framework has recently been extended to the analysis of spillovers from ICT (Stiroh 2002, Mun and Nadiri 2002, Acharya and Basu 2010). In fact, as a GPT, ICT reconciles several explanations of knowledge spillovers. For example, the re-organisation of the production process within firms, fostered by computerization, can be considered the result of learning-by-doing. ICT is also a source of 'pecuniary spillovers' (Griliches 1990)[2] as the combination of competition and innovation in the ICT-producing sector has allowed computer-using industries to benefit from lower costs (Jorgenson, 2001). This source of spillover from the upstream to the downstream sector is also referred to as a *vertical externality* (Bresnahan 1986). Next to this vertical externality we can also identify a *horizontal externality*, 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, internet-based procurement systems and other inter-organisational information systems produces a reduction in administrative and search costs, and a better supply chain management. Atrostic and Nguyen (2005) find evidence on US manufacturing of this "network externality" that arises when the efficiency of products or services increases as they are adopted by more users. This is related to the concept of social learning developed by Aghion (2002) who describes the process of firms' learning about the implementation of a new technology from the experience of other firms. Brynjolfsson et al. (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.

As discussed, the possibilities for ICT spillovers are numerous and can affect companies' performance at different stages of the production process; however, the empirical analysis so far has provided only a weak evidence of such positive externalities. While some studies find significant effects (Mun and Nadiri 2002, van Leeuwen and van der Wiel 2003, Severgnini 2010, Venturini 2011), others reject the existence of spillovers (Stiroh 2002, Acharya and Basu 2010, Van Reenen et al. 2010, Moshiri and Simpson 2011). Stiroh (2002) regresses TFP growth on ICT capital and other controls for the US manufacturing sector over the period 1984-1999. He finds no evidence of ICT capital spillovers, nor evidence of spillovers from individual components (computer capital and telecommunication capital).[3] Haskel and Wallis (2010), using aggregate data for the UK, find no evidence of spillovers from software assets, nor from other intangible assets such as economic competencies and R&D. Similarly, Acharya and Basu (2010) fail to find positive ICT spillovers in a industry-level analysis for 16 OECD countries, but they do find significant spillover effects from domestic and foreign R&D investment.

A possible reason for these results lies in the type of data used in the empirical analysis, with micro data being generally more supportive of the spillover hypothesis compared to industry data.[4] This possibility was recognized by Brynjolfsson and Hitt (2000) and, more recently, by Haskel and Wallis (2010). Firm level studies seem to support this observation. For example, Van Leeuwen and van der Wiel (2003), using a sample of Dutch companies operating in market services, find a positive and significant ICT spillover on labour productivity. In their analysis the introduction of the spillover proxy reduces the size of own firm ICT capital stock, indicating that a considerable part of the ICT impact on labour productivity derives from

spillovers. Similarly, Severgnini (2010) finds evidence of positive ICT spillovers in a sample of Italian manufacturing firms. He also notes that, compared to R&D, ICT can generate spillovers in an unlimited geographical space.

Another stream of research stresses the importance of R&D in enhancing firms' absorptive capacity of the knowledge generated elsewhere (Cohen and Levinthal 1989, Griffith et al. 2004). This suggests the presence of a complementary relationship between firm's R&D and ICT spillovers, which goes beyond the fact that ICT has originated from research effort (Guellec and van Pottelsberghe 2004). The hypothesis that the effect of spillovers depends on facilitating factors in the receiving firms or industries has already been investigated in relation to R&D and human capital (Griffith et al. 2004, Vandenbussche et al. 2006).[5] The evidence on ICT spillovers, however, is still in its infancy and only a handful of studies present some preliminary results, which do not completely clarify the nature of the relationship between the two assets. For example, Hall at al. (2012) find that, although both R&D and ICT contribute to innovation and productivity, they do not complement each other. Using Dutch companies' data, Polder et al. (2010) observe that ICT is unrelated to R&D activities, but significantly influences the organizational innovation of the companies. On the other hand, Greenan et al. (2001) and Matteucci and Sterlacchini (2004) provide evidence of complementarity between computing equipment and research input in French and Italian firms respectively, particularly when considering the cross-sectional dimension of their data. If such complementarity exists but it is not accounted for, there can be a mis-specification problem in existing empirical studies, which can produce a biased ICT spillover coefficient.

The difficulty in identifying spillovers from ICT could also be a consequence of the lagged impact of ICT on productivity. A large empirical literature has shown that ICT adoption imposes long periods of experimentation, during which companies undertake changes in complementary capital, including their organization structure, business practices and customer

relations (Brynjolfsson and Hitt 2003). This implies a substantial delay between initial investments and exploitation of performance improvements, which also justifies a lagged ICT spillover effect. Morrison (2000) shows that, in the US manufacturing sector, returns to high-tech equipment fell below the factor cost share between the1970s and mid-1980s, after which they soared rapidly. In a similar vein, van Ark and Inklaar (2006) find a U-shaped relationship between ICT use and TFP growth across EU and US industries. This pattern suggests that ICT earns normal returns in the early phase of investment, followed by a period of negative effects on TFP; returns to ICT level out to their income share after several years. According to Basu et al. (2004) productivity improvements induced by ICT adoption may materialise with lags of 5 to 15 years, depending on the intensity of investment in complementary inputs. An assessment of the possible lagged effects of ICT on TFP is carried out at firm level by Brynjolfsson and Hitt (2003). Their results show that in a first difference specification ICT does not earn super-normal returns (i.e., it is unrelated to TFP growth); however, with a 7-year difference, the coefficient of ICT capital is 5 times as large as the one emerging in the specification in first differences, supporting the hypothesis that ICT earns excess (or super-normal) returns. Hence a test of the 'delay hypothesis' is necessary to assess the importance of ICT spillovers.

## III. Methodology and data

*A. Modelling the impact of ICT spillovers on productivity*

Our analysis starts from 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. 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. We will evaluate whether companies' productivity performance is affected by the total stock of ICT capital within each industry, and whether this

process is facilitated by the firm (R&D) knowledge base. In doing so, we control for alternative sources of TFP spillovers and assess the presence of various forms of mis-specification.

The starting point of our analysis is a Cobb-Douglas production function,[6] where output ($Y_{ijt}$) is expressed as a function of labour ($L_{ijt}$), capital ($K_{ijt}$), and R&D capital ($R_{ijt}$):

$$Y_{ijt} = A(ICT_{jt})L_{ijt}^{\alpha}K_{ijt}^{\beta}R_{ijt}^{\gamma} \tag{1}$$

where $i$ denotes firm, $j$ industry and $t$ time. Since research expenses cannot be separated from capital and labour outlays, R&D capital is assumed to affect firm output via productivity spillovers. Double counting of research implies that firm output elasticity to own R&D capital is significant only if this factor gains excess returns, i.e. it is source of internal knowledge spillovers (Schankerman1981, Guellec and van Pottelsberghe 2004).The term $A$ is the firm total factor productivity and it is here determined by an industry measure of ICT capital ($ICT_{jt}$). This term will capture the spillovers generated by the diffusion of ICT at the industry level (van Leeuwen and van der Wiel, 2003).[7] Due to data constraints, we are not able to distinguish between ICT and non-ICT capital at the company level, and therefore we cannot separately identify industry-wide spillovers from productivity effect of own digital capital. However, as our measure of company capital embeds ICT assets, the estimation of the spillover effect will not be affected by an omitted variable problem. Furthermore, to control for industry size, we normalize ICT endowment with industry employment. Denoting the log of variables in lower case letters, our empirical specification can be written as (benchmark model):

$$y_{ijt} = a_i + a_t + \alpha l_{ijt} + \beta k_{ijt} + \gamma r_{ijt} + \chi ict_{jt} + \varepsilon_{ijt} \tag{2}$$

where $a_i$ is a company specific intercept (fixed effect), $a_t$ are time dummies. The coefficients $\alpha$ and $\beta$ are standard output elasticities to factor inputs, $\gamma$ identifies productivity externalities related to firm R&D capital (excess returns), $\chi$ captures externalities directly associated with the diffusion of GPT at industry level (measured by ICT capital stock per worker).

We also assess the importance of companies' absorptive capacity in relation to ICT spillovers. Similarly to Griffith et al. (2004) we assume that firms' investments in R&D act not only as an input to the production process but also as a mean to assimilate technological improvements achieved by other companies. To account for absorptive capacity we expand equation (2) to include the interaction between company's R&D and industry ICT:

$$y_{ijt} = a_i + a_t + \alpha l_{ijt} + \beta k_{ijt} + \gamma r_{ijt} + \chi ict_{jt} + \eta r_{ijt} * ict_{jt} + \varepsilon_{ijt} \qquad (3)$$

where $\eta$ is the portion of ICT spillovers acquired by the firm through its knowledge base (i.e. its absorptive capacity). The total impact of ICT spillovers is therefore given by $\chi + \eta\ r_{ijt}$, evaluated at different points of the R&D distribution. Equation (3) models the possibilities that firms may benefit from ICT spillovers by means of their absorptive capacity ($\eta$>0, $\chi$=0), directly without any R&D investments ($\eta$=0, $\chi$>0), or more widely through both channels ($\eta$>0, $\chi$>0).

An important issue in correctly estimating an ICT spillover effect is that there are other factors that can potentially generate spillovers and their impact needs to be accounted for. A prime competitor is R&D spillovers. We therefore expand equation (3) to include a measure of R&D at the industry level ($rd_{jt}$), as follows:

$$y_{ijt} = a_i + a_t + \alpha l_{ijt} + \beta k_{ijt} + \gamma r_{ijt} + \chi ict_{jt} + \eta r_{ijt} * ict_{jt} + \phi rd_{jt} + \varepsilon_{ijt} \qquad (4)$$

where industry level R&D is in per worker terms. As Acharya and Basu (2010) document, this step is crucial as the ICT capital coefficient may be capturing un-measured organizational/intangible inputs. Indeed, when approximating the latter factor with knowledge (R&D) capital, these authors find that ICT capital generates no positive spillovers on industry productivity.

*B. The construction of spillover proxies*

The construction of ICT spillover proxies has generally followed the methodology for the assessment of R&D spillovers, which is often based on the construction of an aggregate

measure, either at the industry or the national level. For example, Van Leuwen and van der Wiel (2003) calculate the spillover term by subtracting a firm's own ICT capital stock from the industry aggregate. Measuring spillovers by introducing an index of aggregate activity is a method that has been widely used in the existing literature (Bernstein and Nadiri, 1989, Caballero and Lyons 1989, 1990, Vecchi 2000). 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 (see Oulton 1996, Pesaran 2006). To address this issue, we introduce time dummies in all estimations ($a_t$). Therefore, any spillover effect will be net of other cyclical and/or exogenous components.

Several contributions also claim that a better spillover proxy can be derived using weighted measures of the pool of external knowledge. These weights are based on different definitions of 'closeness' between firms, such as 'technological' distance (Jaffe 1986), the degree of product market proximity (Bloom et al. 2012) or geographical distance (Lychagin et al. 2010).[8] The latter seem to be more relevant for R&D spillovers rather than spillovers from ICT, since, as discussed in Severgnini (2010), the network effects associated with the use of new information and communications technologies are not confined to a limited geographical space. Alternative weighting approaches account for linkages between suppliers and customers. For example, Mun and Nadiri (2002) construct weighted measures of ICT spillover stocks using industry data on transaction flows across industries from input-output tables.

Our analysis will be based on two spillover proxies for ICT and R&D. First, we use an un-weighted industry measure of ICT/R&D under the assumption that the productivity of a single company is affected by the stock of capital in its own industry. This measure can account for spillovers within the industry (horizontal spillovers) but cannot

capture the presence of spillovers across different industries (vertical spillovers). However, companies may experience productivity gains from innovative practices implemented by their suppliers and customers. To trace such inter-industry flows of spillovers we use industry series on both ICT and R&D capital, weighted by input-output intermediate transactions' coefficients, as follows:

$$wICTL_{jt} = \sum_{j=1}^{17} w_{jft} \times ICTL_{ft} = \sum_{j=1}^{17} \frac{M_{jft}}{Y_{jft}} \times ICTL_{ft} \quad (5)$$

$$wRDL_{jt} = \sum_{j=1}^{17} w_{jft} \times RDL_{ft} = \sum_{j=1}^{17} \frac{M_{jft}}{Y_{jft}} \times RDL_{ft} \quad (6)$$

with $f \neq j$ and $t$=1991, ..., 2001. $ICTL_j$ and $RDL_j$ are respectively ICT and R&D capital stock per worker in the industry $j$ where company $i$ is located. $ICTL_f$ and $RDL_f$ are the value of the surrounding industries ($f \neq j$).[9] $w_{jft}$ is the inter-industry coefficient of intermediate transactions between industry $j$ and industry $f$, defined as ratio between the flow of intermediate inputs sold by industry $f$ to industry $j$ and the gross output of the selling sector, respectively denoted by $M_{jft}$ and $Y_{jft}$. This procedure eliminates the bias associated with the different scale between the 'selling' and the 'purchasing' industry, as discussed in Lichtenberg and van Pottelsberghe (1998) in relation to international technology spillovers. Alternative weighting schemes are considered in the Appendix.

### *C. Data sources and descriptive statistics*

We use US company accounts from the Compustat database for the period 1991-2001. We extract net sales, employment, net physical capital, defined as equipment and structures (PPE), and R&D expenditures. Net physical capital at historic cost is converted into capital at replacement costs (Arellano and Bond 1991). R&D expenditure is 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).[10] The Compustat database classifies companies into industries according to the 1987 US Standard Industrial

Classification (SIC). This classification is then converted into ISIC Rev. 3 base, which is the one followed by industry-level variables. We merge company- and industry-level sources, obtaining a consistent data set for seventeen industries (twelve manufacturing plus five service industries).

Industry accounts data (ICT, employees, etc.) come from EU KLEMS 2011, while R&D expenditure is from OECD ANBERD 2009. Input-output intermediate transactions' coefficients are taken from the OECD I-O output table at benchmark years and are interpolated for intermediate observations.

Table 1 presents descriptive statistics for the variables used in the regression analysis. We work with an unbalanced panel of 968 firms. Over the 1991-2001 period, average net sales amounted to $2,395 million (at 1995 prices), physical capital stock to $780 million, while the cumulative value of R&D was $544 million. On average, US firms employed 11,000 thousands workers. Moving to industry-level variables, we observe that the stock of ICT per worker, *ICTL*, was relatively small with respect to R&D ($4,800 against $39,500 per worker). More interestingly, whereas for ICT assets intra- and inter-industry capital values are comparable in size (*ICTL* vs *wICTL*), the cumulative value of intra-industry R&D sizeably exceeds inter-industry knowledge capital (*RDL* vs *wRDL*). This shows that R&D investment was largely concentrated across sectors while ICT was adopted more pervasively after the digital revolution. It is therefore reasonable to expect heterogeneous effects on firm productivity from these two types of technologically advanced capital.

[Table 1 here]

Table 2 displays industry distributions of firm R&D stock and industry-level variables. Communication services and transport equipment have the highest levels of company knowledge capital ($1,363m and $92,400 per worker), followed by chemicals and business services. In the service industries we observe the highest levels of intra-industry ICT per worker

($ICTL_{jk}$) while inter-industry ICT ($wICTL_{jk}$) is higher in manufacturing industries due to their more intensive inter-industry intermediate transactions.

[Table 2 here]

## IV. Results

### *A. Benchmark specification*

We start our empirical analysis with the estimation of a log linear production function where output is explained by labour, physical capital and R&D capital. We then expand the baseline specification to include our spillover proxies. All estimates are carried out using panel data methods (Fixed Effect estimator) to account for cross sectional heterogeneity. Time dummies are included in all specifications. In all tables we control for the presence of endogeneity by showing results based on a Generalised Method of Moments (GMM) estimator, with lagged values of company variables used as instruments (Hayashi, 2000; Baum et al., 2003); we limit the numbers of lags to two to avoid instrument proliferation and the associated upward bias in estimated coefficients (Roodman 2009). The deterministic elements of the empirical model are treated as exogenous, as well as the industry-level variables. We also correct the covariance matrix for arbitrary heteroskedasticity and for the presence of first-order serial correlation. At the bottom of the each table we report the Kleibergen and Paap (2006) test of under-identification and the Hansen-J (1982) test of over-identifying restrictions. Both tests show that our models are correctly identified and the instruments satisfy the orthogonality conditions.

Table 3 reports our first set of results. In column (1) our estimates for labour and capital elasticity are consistent with prior knowledge of factor shares. Existing evidence on R&D elasticity provides a range of values, from 0.04 (Griliches 1979, 1984, Bloom et al. 2012) to 0.18 (Griliches and Mairesse 1984), and our point estimate of 0.125 lies within this interval. In columns (2-4) we assess the importance of ICT spillovers by including ICT at the industry level,

as in equation (2). We consider intra- and inter-industry spillovers individually (columns 2 and 3) and jointly (Column 4). The two measures produce profoundly different results. Intra-industry spillovers have a negative and significant impact on productivity. These results are consistent, for example, with Stiroh (2002) who finds that ICT capital per employee is negatively related to TFP growth in US manufacturing industries. On the other hand, when we consider the inter-industry effect, the coefficient estimate of our weighted spillover variable is positive and statistically significant and suggests that a 1% increase in ICT investment across all industries raises companies' productivity by approximately 0.21% (see column 4). This effect is not trivial but it does not offset the negative impact from ICT investments within the company's own industry.

The two industry variables appear to pick up different types of technological externalities which affect productivity in the opposite direction. The positive inter-industry effect is likely to capture improved interactions across firms, as discussed in Brynjolfsson et al. (2002). This is also consistent with previous evidence on the ability of information technology to enable productivity spillovers across industries. For example, Mun and Nadiri (2002) find that TFP growth in the US is positively influenced by trade-weighted ICT capital of supplier and customer industries. Additionally, Wolff (2011) shows that, as long as information technology spreads out through the US economy, knowledge spillovers become an increasingly important source of TFP growth. Similarly, Bernstein (2000) shows that communication infrastructure acts as a conduit of R&D spillovers from the United States to the Canadian manufacturing sector.[11]

The negative productivity effect from (intra-)industry ICT may be due to two possible causes. First, the new technology requires a re-organisation of the production process which implies large adjustment costs for companies, particularly in the initial stage of diffusion (Bresnahan 2003, Kiley, 2001). Second, it is possible that the negative sign of own-industry ICT

investment is due to a business stealing effect, whereby companies that find new and more efficient applications by ICT usage will negatively affect the productivity of their competitors (Bloom et al. 2012).[12] We will further elaborate these two explanations later in the work.[13] In the next section we further investigate these results addressing two possible types of mis-specification which could affect the estimation of our benchmark model: the existence of complementarities between companies' R&D and ICT spillovers and the presence of a lagged ICT spillover effect.

[Table 3 here]

*B. ICT spillovers and absorptive capacity*

In this section we extend our model to account for the role of absorptive capacity, i.e. the firm's ability to use the technology developed elsewhere. Our main hypothesis is that such absorptive capacity is a function of the firm's own investment in R&D, i.e. more innovative firms are better equipped with the necessary skills and resources to take advantage of the new technology. This phenomenon is captured by the introduction of an interaction between companies' R&D and the two spillover proxies, as described in Equation (3). A positive and significant coefficient on the interaction term would provide evidence of productivity spillovers from ICT capital via the firm's absorptive capacity, revealing a complementarity between the technology endowment of the company and that of the environment in which it operates.

[Table 4 here]

Table 4 presents the results of the estimation of equation (3). Our estimates of the interaction term are positive and significant both when considering intra- and inter-industry spillovers, hence confirming the mutually self-enforcing effect of firm's innovative effort and industry ICT capital (Columns 1-2). However, in column 3, when we account for both effects in the same specification, the interaction between firms' R&D and inter-industry ICT is no longer statistically significant. Additionally, the coefficient on companies' R&D goes from 0.043 (not

significant) in column 2, to 0.229 and significant in column 3. This is likely to be the result of a collinearity problem between the two interaction terms (the correlation coefficient between the two interaction terms is 0.71). For these reasons, in the reminder of our analysis we will only include the interaction between own-company R&D and intra-industry ICT spillovers, i.e. we will carry on with the specification presented in column 4.

Following the discussion in section 3.A, we compute the total intra-industry spillover evaluating the interaction effect at different points of the companies' R&D distribution. The results are presented at the bottom of Table 4, where we also report the overall spillover (intra + inter industry). Despite the positive interaction, the total intra-industry spillover effect remains negative, although decreasing with the size of firm’s knowledge base. The total spillover effect from ICT, given by the sum of total intra- and inter-industry effects, is therefore negative for the majority of the companies. Only for those at the upper tail of the distribution (over the 95th percentile), intra-industry spillovers were exactly compensated by positive impact of inter-industry ICT externalities. In other words, at the outset of the information age, the negative effects of ICT associated with business-stealing or restructuring appear to prevail on TFP-enhancing impact for a typical US company.

*C. The lagged effect of ICT spillovers*

The previous sections showed that in the 1990s US companies did not gain productivity benefits from ICT adoption within the industry in which they operated, and that two competing explanations may be behind such an effect (restructuring and business-stealing). The restructuring hypothesis is particularly popular in the ICT literature. Indeed, the main benefits of ICT are related to their networking and learning abilities (information management, data exchange, firm connectivity, diffusion of best practices, etc.), and firms need to re-organize their business to fully benefit from technological advancements of contiguous companies.

Here, we further investigate the restructuring hypothesis by controlling for the lagged impact of ICT spillovers on productivity. As discussed in Aghion (2002) among others, the adoption of ICT imposes long periods of experimentation during which the firm (or the industry) typically learns the new technology from the experience of others. To test the "lagged ICT spillover hypothesis" we re-estimate equation (3) using lagged values of all the ICT spillover proxies (Table 5). Col. (1) displays our key findings from Table 4 for comparison purposes; in columns 2-4 we report estimates obtained considering different lags for the ICT spillover variables, i.e. all industry-level variables and interactions taken with 1-, 3- and 5-year lags.

[Table 5 here]

Results in Table 5 change dramatically when we consider different lags of the spillover variables. At time *t-1* we still have a negative intra-industry ICT spillover and a positive inter-industry effect. The former is still negative, but of smaller magnitude, at time *t-3*. However, when we consider the 5-year lag specification both intra- and inter-industry effects of information technology are positive and significant.

At the bottom of Table 5 we compute the total ICT spillover effects for different values of companies' R&D capital, based on the estimates in column 4 (i.e 5-year lag specification). It shows that all companies gain positive and significant productivity spillovers from industry ICT. The implied overall effect is not trivial: a 1% increase in industry ICT increases companies' productivity by approximately 0.4%. Furthermore, spillovers are identical for all companies, irrespective of their knowledge base and absorptive capacity. This result implies that, over time, the importance of the complementarity between company R&D and industry ICT decreases and it eventually becomes statistically insignificant. Hence, while in the short run firms' absorptive capacity is necessary to reap the benefits of the new technology, over time the technology becomes more established and the benefits from spillovers are more widespread.

[Table 6 here]

To further investigate the relationship between absorptive capacity and ICT spillovers we compute the R&D threshold level (in percentiles) at which total ICT spillover turns from negative (or insignificant) to positive values in any single specification of Table 5, based on different lags of ICT variables. These results, reported in Table 6, clearly show that contemporaneous effects are negligible and only companies at the higher end of the R&D distribution are able to off-set the negative impact of ICT spillovers, related to the restructuring process; hence for this group of firms, total effect of ICT on productivity growth is statistically irrelevant. After only 3 years from investment, overall spillovers of ICT materialize with a positive effect for at least 25% of US companies. Considering 5-year lags, the magnitude of this effect increases and the threshold level of R&D reduces considerably; in essence, even companies with a very low R&D capital enjoy significant returns from ICT spillovers.

## V. Robustness checks

In this section we further extend our production function specification to account for other factors that are related to productivity enhancement and whose absence could bias the coefficient estimates of the spillover variables. Firstly, we introduce proxies for R&D spillovers, following the methodology discussed in section 3. Table 7 presents our results. In column 1, we find a positive intra-industry R&D spillover effect, while the ICT spillover impacts on productivity are still strong and significant. In column 2 we introduce the inter-industry R&D spillover but this variable generates an unexpected result, being negative and strongly significant. This is hard to justify in the light of existing evidence of positive knowledge spillovers in the US economy in the same time period (Bloom et al. 2012). This result is more likely caused by an over-parameterisation of the model presented in column 2, with the effect of the industry variables overlapping with each other.[14] In fact, not only does the

intra-industry R&D spillover become statistically insignificant, but the coefficient on inter-industry ICT becomes twice as large as the coefficient reported in column 1 (0.448 versus 0.207). We therefore continue with a more conservative estimate of the ICT spillover effect and carry on the analysis with the sole inclusion of the intra-industry R&D spillover (as in column 1).

Secondly, we include in our specification the industry total hours worked, to capture the impact of cyclical labour utilization on productivity. Existing empirical evidence shows that variations in labour effort over the cycle can be mistaken for spillover effects (Hall 1989, Vecchi 2000) and it is therefore important to account for this additional source of productivity growth. More recently, Oliner et al. (2008) suggested that the resurgence in labour productivity in the 1990s could be caused by normal cyclical dynamics. Column 3 reports results for the contemporaneous spillover effect, while columns 4-6 reports coefficient estimates for the specification with lagged spillovers.

[Table 7 here]

The results on the ICT spillover variables are generally consistent across the different specifications, with the exception of the 3-year lag model (column 5) where the intra-industry ICT is no longer significant. This implies that the total spillover effect from ICT is positive, independently of the level of companies' own R&D capital. The coefficient on the R&D spillover variable is statistically significant up to the 1-year lag specification. Further lags do not significantly affect productivity performance. Hence, our results suggest that the effect of industry R&D and ICT spillovers materialises with a different timing on company productivity.

As a further robustness check we also considered an alternative specification where we only lagged the ICT spillover variables. Our results remained virtually unchanged. This excludes the possibility that the effect of ICT somehow captures un-measured complementary factors such as intangible or organisational assets, contradicting the argument put forward by

Acharya and Basu (2010). In the Appendix, we show that results of Table 7 are robust considering alternative weights for inter-industry ICT spillovers.

## VI. Conclusions

This paper has provided new evidence on the presence of ICT spillovers in the US economy in the 1990s, and on the complementarity between industry ICT spillovers and companies' innovative effort. We have constructed two measures of ICT externalities and considered both contemporaneous and lagged spillover effects, with the aim of assessing the complex way in which ICT has affected firm performance. Contemporaneous effects are mixed: inter-industry spillovers, which primarily capture network effects, are positive while intra-industry spillovers are negative, a consequence of firms' restructuring process. This suggests that in earlier stages of diffusion, ICT may have favoured connectivity with upstream and downstream sectors, but it did not positively contribute to firms' productivity growth within the sector. The total spillover effect is negative, although the complementarity between ICT and companies' R&D investments allows the most innovative companies to offset the negative intra-industry spillovers.

Our conclusions change when we allow for lagged spillovers. In fact, our results show that all companies are able to reap the benefit from both intra- and inter-industry ICT with approximately a 5-year lag. Within the same time frame, the complementarity between companies' R&D and industry ICT loses its importance, which suggests that in the long run the impact of the new technology is pervasive. These results are in line with the hypothesis of the "delayed effects" of ICT on productivity growth and support the GPT prediction that the benefits of a new technology become stronger over time. Our results are robust to the inclusion of R&D spillovers, cyclical labour utilization and alternative proxies for ICT spillovers. Further

research is nonetheless needed to assess the importance of ICT spillovers when one considers different countries and different time periods.

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## APPENDIX

### 1. Additional robustness checks

This section reports some additional robustness checks for the key results of Table 7, based on alternative weighting schemes for the inter-industry ICT spillover variable. The key findings shown in the main text, based on contemporaneous and 5-year lagged values of industry variables, are reported in cols. 1-2 of Table A.1 for ease of comparison. The weighting factor in the construction of the inter-industry ICT capital used in this set of results is given by the ratio between intermediate transactions among industries $j$ and $f$ ($M_{jft}$) and total intermediates' sales of the selling industry ($Y_{ft}$). Equation (A.1) below reproduces equation (5) in the main text:

$$wICTL_{jt} = \sum_{j=1}^{17} w_{jft} \times ICTL_{ft} = \sum_{j=1}^{17} \frac{M_{jft}}{Y_{ft}} \times ICTL_{ft}. \tag{A.1}$$

Alternatively, we can construct a weighting factor by dividing inter-industry intermediate transactions by the total intermediate purchases of the buying industry ($P_{jt}$). We call this measure $wICT_{jt}^{b}$, where 'b' stands for 'buyer':

$$wICTL_{jt}^{b} = \sum_{j=1}^{17} w_{jft}^{b} \times ICTL_{ft} = \sum_{j=1}^{17} \frac{M_{jft}}{P_{jt}} \times ICTL_{ft} \tag{A.2}$$

Results based on this measure are presented in cols. (3)-(4) of Table A.1. These estimates broadly confirm our baseline findings, even though the inter-industry ICT spillover appears somewhat higher.

We also test the robustness of our results to the use of a weighting scheme based on inter-industry patent citations. Indeed, one may question that the ability to exploit technology improvements of the surrounding industries may depend on technological proximity of sectors, rather than the intensity of their trade transactions. For this reason, we build inter-industry patent citation matrix flows using NBER USPTO patent data files 2006 (see Hall et al. 2001 for details). We consider two versions of this patent based ICT spillover measure (denoted by 'p'), following the two alternative weighting methodologies shown above. In equation (A.3), the

weighting factor ($w^{p}_{jft}$) is the ratio between the citations made by patent assignees operating in industry *j* to patents applied for firms operating in industry *f* ($C_{jft}$) and total (backward) citations made by industry *j* ($C_{jt}$):

$$wICTL^{p}_{jt} = \sum_{j=1}^{12} w^{p}_{jft} \times ICTL_{ft} = \sum_{j=1}^{12} \frac{C_{jft}}{C_{ft}} \times ICTL_{ft}. \quad \text{(A.3)}$$

In equation (A.4) the weighting factor is scaled by the total (forward) citations received by industry *f* ($C_{ft}$):

$$wICTL^{p,b}_{jt} = \sum_{j=1}^{12} w^{p,b}_{jft} \times ICTL_{ft} = \sum_{j=1}^{12} \frac{C_{jft}}{C_{jt}} \times ICTL_{ft}. \quad \text{(A.4)}$$

Equation (A.3) defines the inter-industry ICT spillover variable using weights reflecting the total amount of knowledge "released" by contiguous industries ($wICT^{b}_{jt}$). Equation (A.4) considers as a scale factor the total amount of knowledge "acquired" by the recipient industry $wICT^{p,b}_{jt}$. Results based on these patent-weighted measures of spillovers are presented in columns 5-8 of Table A.1. These only refer to the manufacturing sector as there is no information on patents for services.

It is interesting to observe from cols. (5)-(6) and (7)-(8) that our key results are fully confirmed, and that the inter-industry ICT spillover is stronger when considering technological closeness among sectors. In the light of all these results, the inter-industry spillover of ICT capital discussed in the main text is clearly more conservative and can be regarded as a lower bound.

[Table A.1 here]

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TABLE 1. DESCRIPTIVE STATISTICS (1991-2001)

| | | Obs | Mean | SD | Min | Max |
|---|---|---|---|---|---|---|
| *Company characteristics* | | | | | | |
| $Y_{ijt}$ | Output | 9,435 | 2,395 | 9,549 | 0.026 | 181,078 |
| $L_{ijt}$ | Employees (thousands) | 9,065 | 11 | 36 | 0.004 | 756 |
| $K_{ijt}$ | Physical capital | 9,465 | 780 | 3,485 | 0.007 | 81,143 |
| $R_{ijt}$ | R&D capital | 9,480 | 544 | 2,445 | 1.008 | 44,971 |
| *Industry characteristics* (thousands) | | | | | | |
| $ICTL_{jt}$ | Intra-industry ICT capital (p.w.) | 9,480 | 4.8 | 5.1 | 0.092 | 36.7 |
| $wICTL_{jt}$ | Inter-industry ICT capital (p.w.) | 9,480 | 3.9 | 3.3 | 0.494 | 18.2 |
| $RDL_{jt}$ | Intra-industry R&D capital (p.w.) | 9,480 | 39.5 | 43.1 | 0.006 | 112.5 |
| $wRDL_{jt}$ | Inter-industry R&D capital (p.w.) | 9,480 | 10.6 | 13.3 | 1.273 | 52.9 |

Notes: Employees are measured in thousands. All other variables are expressed in millions of 1995 USD, unless otherwise specified. Industry values are expressed per unit of workers (p.w.).

TABLE 2. AVERAGE COMPANY R&D AND SPILLOVER PROXIES BY INDUSTRY (1991-2001)

| | | Obs | $R_{ijk}$ (millions of USD) | $ICTL_{jk}$ | $wICTL_{jk}$ | $RDL_{jk}$ | $wRDL_{jk}$ |
|---|---|---|---|---|---|---|---|
| | | | | (Thousands of USD per worker) | | | |
| *15t16* | Food & Beverage | 160 | 335 | 2.0 | 4.5 | 4.8 | 8.0 |
| *17t19* | Textile, Clothing & Footwear | 107 | 64 | 0.7 | 7.0 | 1.4 | 44.2 |
| *20* | Wood | 32 | 175 | 0.6 | 1.6 | 0.2 | 6.1 |
| *21t22* | Pulp, Paper & Publishing | 216 | 457 | 2.5 | 2.2 | 4.2 | 6.2 |
| *24* | Chemicals | 1,374 | 836 | 8.6 | 2.3 | 91.0 | 2.8 |
| *25* | Rubber &Plastics | 33 | 775 | 1.0 | 3.1 | 8.8 | 24.3 |
| *26* | Non-metallic minerals | 44 | 68 | 2.2 | 1.3 | 6.8 | 5.0 |
| *27t28* | Basic metals, etc. | 129 | 52 | 1.6 | 1.3 | 5.0 | 5.0 |
| *29* | Machinery | 741 | 192 | 3.7 | 4.8 | 17.0 | 20.9 |
| *30t33* | Electrical equipment | 3,676 | 382 | 5.2 | 4.2 | 87.7 | 8.2 |
| *34t35* | Transport equipment | 903 | 1,363 | 3.2 | 9.2 | 92.4 | 48.8 |
| *36t37* | Manufacturing, nec | 382 | 133 | 1.2 | 4.7 | 8.5 | 17.6 |
| *50t52* | Wholesale, Retail | 124 | 84 | 1.4 | 4.2 | 1.6 | 7.2 |
| *55* | Hotels, Restaurant | 7 | 104 | 0.2 | 6.1 | 0.4 | 6.7 |
| *64* | Communications | 43 | 4,387 | 20.7 | 1.3 | 2.3 | 4.3 |
| *65t67* | Financial services | 51 | 46 | 10.4 | 4.1 | 0.9 | 2.3 |
| *71t74* | Business services | 1,458 | 532 | 3.8 | 1.8 | NA | 2.6 |
| *15t74* | TOTAL ECONOMY* | 9,480 | 543.7 | 4.8 | 3.9 | 39.5 | 10.6 |

Notes: *excludes real estate activities.

TABLE 3. PRODUCTION FUNCTION ESTIMATION WITH ICT SPILLOVERS

| | (1) | (2) | (3) | (4) |
|---|---|---|---|---|
| *Company level variables* | | | | |
| Employment ($\alpha$) | 0.765*** | 0.783*** | 0.774*** | 0.790*** |
| | (0.034) | (0.035) | (0.035) | (0.035) |
| Physical capital ($\beta$) | 0.120*** | 0.109*** | 0.119*** | 0.110*** |
| | (0.026) | (0.026) | (0.026) | (0.026) |
| R&D capital ($\gamma$) | 0.125*** | 0.135*** | 0.111*** | 0.119*** |
| | (0.020) | (0.021) | (0.021) | (0.021) |
| *Industry level variables* | | | | |
| Intra-industry ICT ($\chi_1$) | | -0.378*** | | -0.330*** |
| | | (0.040) | | (0.039) |
| Inter-industry ICT ($\chi_2$) | | | 0.258*** | 0.206*** |
| | | | (0.036) | (0.034) |
| Obs | 6,876 | 6,745 | 6,704 | 6,704 |
| R-squared | 0.756 | 0.758 | 0.757 | 0.760 |
| No. of Firms | 968 | 945 | 938 | 938 |
| Kleibergen-Paap LM stat P-value | <0.001 | <0.001 | <0.001 | <0.001 |
| Hansen J test P-value | 0.135 | 0.308 | 0.187 | 0.322 |

All equations are estimated using a GMM Fixed effects estimator. Time dummies are included in all specifications. Standard errors robust to heteroskedasticity and first-order serial correlation reported in parentheses. The dependent variable is log output (total sales). All company level variables have been instrumented with their own values at time t-1 and t-2. In the presence of heteroscedasticity, the Hansen J statistic is an appropriate test of the null hypothesis of instrument validity. The Kleibergen-Paap LM statistic tests the null hypothesis that the matrix of reduced-form coefficients in the first-stage regression is under-identified. ***, **, * significant at 1, 5 and 10%.

TABLE 4. ICT SPILLOVER AND ABSORPTIVE CAPACITY

| | (1) | (2) | (3) | (4) |
|---|---|---|---|---|
| *Company level variables* | | | | |
| Employment ($\alpha$) | 0.781*** | 0.772*** | 0.790*** | 0.788*** |
| | (0.035) | (0.035) | (0.035) | (0.035) |
| Physical capital ($\beta$) | 0.112*** | 0.123*** | 0.112*** | 0.114*** |
| | (0.026) | (0.027) | (0.027) | (0.026) |
| R&D capital ($\gamma$) | 0.111*** | 0.043 | 0.229** | 0.098*** |
| | (0.022) | (0.043) | (0.114) | (0.023) |
| *Industry level variables and interactions* | | | | |
| Intra-industry ICT ($\chi_1$) | -0.441*** | | -0.525*** | -0.390*** |
| | (0.044) | | (0.15) | (0.043) |
| Firm R&D*intra-industry ICT ($\eta_1$) | 0.014*** | | 0.039* | 0.0129*** |
| | (0.004) | | (0.020) | (0.004) |
| Inter-industry ICT ($\chi_2$) | | 0.221*** | 0.287*** | 0.202*** |
| | | (0.040) | (0.074) | (0.034) |
| Firm R&D*inter-industry ICT ($\eta_2$) | | 0.008** | -0.021 | |
| | | (0.004) | (0.017) | |
| Obs. | 6,745 | 6,704 | 6,704 | 6,704 |
| R-squared | 0.759 | 0.758 | 0.760 | 0.761 |
| No. of Firms | 945 | 938 | 938 | 938 |
| Kleibergen-Paap LM statistic P-value | <0.001 | <0.001 | <0.001 | <0.001 |
| Hansen J test P-value | 0.318 | 0.191 | 0.335 | 0.321 |

TOTAL ICT SPILLOVER EFFECT (ESTIMATES FROM COLUMN 4)

| | **Percentile** | **1%** | **5%** | **10%** | **25%** | **50%** | **75%** | **90%** | **95%** | **99%** |
|---|---|---|---|---|---|---|---|---|---|---|
| | *Ln(R&D)* | 0.35 | 1.23 | 1.92 | 3.00 | 4.10 | 5.23 | 6.64 | 7.69 | 9.12 |
| *a* | $\eta_1$**ln(RD)* | 0.00 | 0.02 | 0.02 | 0.04 | 0.05 | 0.07 | 0.09 | 0.10 | 0.12 |
| *b* | *Intra-industry* ($\chi_1$) | -0.39 | -0.39 | -0.39 | -0.39 | -0.39 | -0.39 | -0.39 | -0.39 | -0.39 |
| *c=a+b* | *Total Intra-industry* | -0.39 | -0.37 | -0.37 | -0.35 | -0.34 | -0.32 | -0.30 | -0.29 | -0.27 |
| *d* | *Inter industry* ($\chi_2$) | 0.20 | 0.20 | 0.20 | 0.20 | 0.20 | 0.20 | 0.20 | 0.20 | 0.20 |
| *e=c+d* | *Total ICT effect* | -0.18 | -0.17 | -0.16 | -0.15 | -0.14 | -0.12 | -0.10 | -0.09 | -0.07 |
| | *P-value* | [0.00] | [0.00] | [0.00] | [0.00] | [0.01] | [0.02] | [0.05] | [0.09] | [0.19] |

All equations are estimated using a GMM Fixed effects estimator. Time dummies are included in all specifications. Standard errors robust to heteroskedasticity and first-order serial correlation reported in parentheses. The dependent variable is log output (total sales). All company level variables have been instrumented with their own values at time t-1 and t-2. In the presence of heteroscedasticity, the Hansen J statistic is an appropriate test of the null hypothesis of instrument validity. The Kleibergen-Paap LM statistic tests the null hypothesis that the matrix of reduced-form coefficients in the first-stage regression is under-identified. ***, **, * significant at 1, 5 and 10%.

TABLE 5. LAGGED ICT SPILLOVERS AND COMPANIES' PRODUCTIVITY PERFORMANCE

| | (1) | (2) | (3) | (4) |
|---|---|---|---|---|
| | *Contemporaneous effect* | 1-year lag | 3-year lag | 5-year lag |
| *Company level variables* | | | | |
| Employment ($\alpha$) | 0.788*** | 0.783*** | 0.780*** | 0.840*** |
| | (0.035) | (0.035) | (0.043) | (0.072) |
| Physical capital ($\beta$) | 0.114*** | 0.120*** | 0.110*** | 0.048 |
| | (0.026) | (0.026) | (0.031) | (0.049) |
| R&D capital ($\gamma$) | 0.098*** | 0.0939*** | 0.115*** | 0.114*** |
| | (0.023) | (0.022) | (0.024) | (0.034) |
| *Industry level variables and interactions* | | | | |
| Intra-industry ICT ($\chi_1$) | -0.390*** | -0.415*** | -0.196*** | 0.266*** |
| | (0.043) | (0.046) | (0.060) | (0.094) |
| Firm R&D*intra-industry ICT ($\eta_1$) | 0.0129*** | 0.0160*** | 0.0139*** | -0.007 |
| | (0.004) | (0.004) | (0.005) | (0.009) |
| Inter-industry ICT ($\chi_2$) | 0.202*** | 0.192*** | 0.230*** | 0.173*** |
| | (0.034) | (0.032) | (0.036) | (0.043) |
| Obs. | 6,704 | 6,704 | 5,893 | 4,093 |
| R-squared | 0.761 | 0.761 | 0.727 | 0.627 |
| No. of Firms | 938 | 938 | 915 | 816 |
| Kleibergen-Paap LM statistic P-value | <0.001 | <0.001 | <0.001 | <0.001 |
| Hansen J test P-value | 0.321 | 0.279 | 0.163 | 0.717 |

TOTAL ICT SPILLOVER EFFECT (ESTIMATES FROM COLUMN 4)

| | **Percentile** | **1%** | **5%** | **10%** | **25%** | **50%** | **75%** | **90%** | **95%** | **99%** |
|---|---|---|---|---|---|---|---|---|---|---|
| | *Ln(R&D)* | 0.35 | 1.23 | 1.92 | 3.00 | 4.10 | 5.23 | 6.64 | 7.69 | 9.12 |
| *a* | $\eta_1$*ln(RD)* | 0.00 | -0.01 | -0.01 | -0.02 | -0.03 | -0.04 | -0.05 | -0.05 | -0.06 |
| *b* | *Intra-industry* ($\chi_1$) | 0.27 | 0.27 | 0.27 | 0.27 | 0.27 | 0.27 | 0.27 | 0.27 | 0.27 |
| *c=a+b* | *Total Intra-industry* | 0.26 | 0.26 | 0.25 | 0.25 | 0.24 | 0.23 | 0.22 | 0.21 | 0.20 |
| *d* | *Inter-industry*($\chi_2$) | 0.17 | 0.17 | 0.17 | 0.17 | 0.17 | 0.17 | 0.17 | 0.17 | 0.17 |
| *e=c+d* | *Total ICT effect* | 0.44 | 0.43 | 0.43 | 0.42 | 0.41 | 0.40 | 0.39 | 0.39 | 0.38 |
| | *P-value* | [0.00] | [0.00] | [0.00] | [0.00] | [0.00] | [0.00] | [0.00] | [0.00] | [0.00] |

All equations are estimated using a GMM Fixed effects estimator. Time dummies are included in all specifications. Standard errors robust to heteroskedasticity and first-order serial correlation reported in parentheses. The dependent variable is log output (total sales). All company level variables have been instrumented with their own values at time t-1 and t-2. In the presence of heteroscedasticity, the Hansen J statistic is an appropriate test of the null hypothesis of instrument validity. The Kleibergen-Paap LM statistic tests the null hypothesis that the matrix of reduced-form coefficients in the first-stage regression is under-identified. ***, **, * significant at 1, 5 and 10%.

TABLE 6. IDENTIFICATION OF R&D THRESHOLD PERCENTILES FROM REGRESSIONS USING DIFFERENT LAGS OF ICT VARIABLES

| | *Contemporaneous effect* | *1-year lag* | *3-year lag* | *5-year lag* |
|---|---|---|---|---|
| | **95%** | **95%** | **75%** | **1%** |
| R&D threshold level (C), in logs | 7.69 | 7.69 | 5.23 | 0.35 |
| Coefficient | -0.09 | -0.10 | 0.11 | 0.36 |
| P-value | [0.09] | [0.06] | [0.08] | [0.00] |
| Below *C* | Negative | Negative | Insignificant | - |
| Above *C* | Insignificant | Insignificant | Positive | Positive |

Notes: these values are obtained from the estimates in table 5. The p-value refers to the test of the null hypothesis that total ICT spillover effect is zero.

TABLE 7. CONTROLLING FOR R&D SPILLOVERS

| | (1) | (2) | (3) | (4) | (5) | (6) |
|---|---|---|---|---|---|---|
| | *Contemporaneous effects* | | | *Lagged spillover effects* | | |
| | | | | *1-year lag* | *3-year lag* | *5-year lag* |
| *Company level variables* | | | | | | |
| Employment ($\alpha$) | 0.793*** | 0.793*** | 0.789*** | 0.789*** | 0.796*** | 0.840*** |
| | (0.039) | (0.039) | (0.039) | (0.039) | (0.048) | (0.079) |
| Physical capital ($\beta$) | 0.114*** | 0.115*** | 0.115*** | 0.117*** | 0.102*** | 0.0440 |
| | (0.030) | (0.030) | (0.030) | (0.030) | (0.035) | (0.055) |
| R&D capital ($\gamma$) | 0.092*** | 0.090*** | 0.093*** | 0.092*** | 0.120*** | 0.132*** |
| | (0.025) | (0.025) | (0.025) | (0.025) | (0.0261) | (0.0355) |
| *Industry level variables and interactions* | | | | | | |
| Intra-industry ICT ($\chi$1) | -0.494*** | -0.371*** | -0.410*** | -0.374*** | 0.0389 | 0.330*** |
| | (0.057) | (0.065) | (0.060) | (0.058) | (0.069) | (0.104) |
| Firm R&D*intra-industry ICT ($\eta_1$) | 0.014*** | 0.016*** | 0.015*** | 0.018*** | 0.014** | -0.007 |
| | (0.005) | (0.005) | (0.005) | (0.005) | (0.005) | (0.009) |
| Inter-industry ICT ($\chi_2$) | 0.207*** | 0.448*** | 0.198*** | 0.169*** | 0.159*** | 0.145*** |
| | (0.034) | (0.092) | (0.038) | (0.036) | (0.043) | (0.049) |
| Intra-industry R&D ($\phi_1$) | 0.046** | 0.029 | 0.043** | 0.034* | -0.005 | -0.022 |
| | (0.019) | (0.019) | (0.018) | (0.0176) | (0.020) | (0.033) |
| Inter-industry R&D ($\phi_2$) | | -0.289*** | | | | |
| | | (0.091) | | | | |
| Hours worked ($\rho$) | | | 0.385*** | 0.407*** | 0.946*** | 0.821*** |
| | | | (0.141) | (0.134) | (0.158) | (0.188) |
| Obs. | 5814 | 5814 | 5814 | 5,814 | 5,128 | 3,616 |
| R-squared | 0.743 | 0.744 | 0.744 | 0.743 | 0.709 | 0.622 |
| No. of Firms | 785 | 785 | 785 | 785 | 770 | 708 |
| Kleibergen-Paap LM test P-value | <0.001 | <0.001 | <0.001 | <0.001 | <0.001 | <0.001 |
| Hansen J test P-value | 0.451 | 0.474 | 0.471 | 0.427 | 0.446 | 0.857 |

TOTAL ICT SPILLOVER EFFECT (ESTIMATES FROM COLUMN 6)

| | **Percentile** | **1%** | **5%** | **10%** | **25%** | **50%** | **75%** | **90%** | **95%** | **99%** |
|---|---|---|---|---|---|---|---|---|---|---|
| | *Ln(R&D)* | 0.35 | 1.23 | 1.92 | 3.00 | 4.10 | 5.23 | 6.64 | 7.69 | 9.12 |
| a | *Abs*ln(RD)* | 0.00 | -0.01 | -0.01 | -0.02 | -0.03 | -0.04 | -0.05 | -0.05 | -0.06 |
| b | *Inter-industry* | 0.33 | 0.33 | 0.33 | 0.33 | 0.33 | 0.33 | 0.33 | 0.33 | 0.33 |
| c=a+b | *Total Intra-industry* | 0.33 | 0.32 | 0.32 | 0.31 | 0.30 | 0.29 | 0.28 | 0.28 | 0.27 |
| d | *Inter-industry* | 0.15 | 0.15 | 0.15 | 0.15 | 0.15 | 0.15 | 0.15 | 0.15 | 0.15 |
| e=c+d | *Total ICT effect* | 0.47 | 0.47 | 0.46 | 0.45 | 0.45 | 0.44 | 0.43 | 0.42 | 0.41 |
| | *P-value* | [0.00] | [0.00] | [0.00] | [0.00] | [0.00] | [0.00] | [0.00] | [0.00] | [0.00] |

All equations are estimated using a Fixed effects (FE) estimator. Time dummies are included in all specifications. Standard errors robust to heteroskedasticity and first-order serial correlation reported in parentheses. The dependent variable is log output (total sales). All company level variables have been instrumented with their own values at time t-1 and t-2. In the presence of heteroscedasticity, the Hansen J statistic is an appropriate test of the null hypothesis of instrument validity. The Kleibergen-Paap LM statistic tests the null hypothesis that the matrix of reduced-form coefficients in the first-stage regression is under-identified. ***, **, * significant at 1, 5 and 10%.

TABLE A.1: ROBUSTNESS CHECKS FOR THE EXTENDED PRODUCTION FUNCTION BASED ON ALTERNATIVE WEIGHTING SCHEMES

| Weighting scheme | *All* I-O transactions on total sales (A.1) | | *All* I-O transactions on total intermediate purchases (A.2) | | *Manufacturing* Total backward patent citations scaled on cited industry (A.3) | | *Manufacturing* Total backward patent citations scaled on citing industry (A.4) | |
|---|---|---|---|---|---|---|---|---|
| | (1) | (2) | (3) | (4) | (5) | (6) | (7) | (8) |
| | *Contempo-raneous* | *5-year lag* | *Contempo-raneous* | *5-year lag* | *Contempo-raneous* | *5-year lag* | *Contempo-raneous* | *5-year lag* |
| *Company level variables* | | | | | | | | |
| Employment ($\alpha$) | 0.789*** | 0.840*** | 0.783*** | 0.842*** | 0.779*** | 0.840*** | 0.782*** | 0.840*** |
| | (0.039) | (0.079) | (0.039) | (0.079) | (0.040) | (0.080) | (0.040) | (0.079) |
| Physical capital ($\beta$) | 0.115*** | 0.0440 | 0.110*** | 0.035 | 0.118*** | 0.038 | 0.118*** | 0.039 |
| | (0.030) | (0.055) | (0.030) | (0.055) | (0.030) | (0.0555) | (0.030) | (0.055) |
| R&D capital ($\gamma$) | 0.093*** | 0.132*** | 0.111*** | 0.145*** | 0.107*** | 0.144*** | 0.090*** | 0.140*** |
| | (0.025) | (0.0355) | (0.024) | (0.035) | (0.025) | (0.036) | (0.025) | (0.036) |
| *Industry level variables and interactions* | | | | | | | | |
| Intra-industry ICT ($\chi 1$) | -0.410*** | 0.330*** | -0.323*** | 0.368*** | -0.229*** | 0.320*** | -0.160** | 0.322*** |
| | (0.060) | (0.104) | (0.058) | (0.106) | (0.064) | (0.105) | (0.065) | (0.105) |
| Firm R&D*intra-industry ICT ($\eta_1$) | 0.015*** | -0.007 | 0.0125*** | -0.008 | 0.014*** | -0.007 | 0.016*** | -0.007 |
| | (0.005) | (0.009) | (0.005) | (0.009) | (0.005) | (0.009) | (0.005) | (0.009) |
| Inter-industry ICT ($\chi_2$) | 0.198*** | 0.145*** | 0.482*** | 0.266** | 0.499*** | 0.315*** | 0.358*** | 0.173*** |
| | (0.038) | (0.049) | (0.106) | (0.119) | (0.123) | (0.118) | (0.051) | (0.044) |
| Intra-industry R&D ($\phi_1$) | 0.043** | -0.022 | 0.032 | -0.025 | 0.087** | 0.027 | 0.080** | -0.007 |
| | (0.018) | (0.033) | (0.022) | (0.033) | (0.035) | (0.037) | (0.035) | (0.035) |
| Hours worked ($\rho$) | 0.385*** | 0.821*** | 0.385*** | 0.862*** | 0.660*** | 0.823*** | 0.486*** | 0.782*** |
| | (0.141) | (0.188) | (0.144) | (0.195) | (0.148) | (0.189) | (0.144) | (0.186) |
| Obs. | 5814 | 3,616 | 5,814 | 3,616 | 5,680 | 3,545 | 5,680 | 3,545 |
| R-squared | 0.744 | 0.622 | 0.744 | 0.621 | 0.745 | 0.623 | 0.746 | 0.624 |
| No. of Firms | 785 | 708 | 785 | 708 | 761 | 692 | 761 | 692 |
| Kleibergen-Paap LM test P-value | <0.001 | <0.001 | <0.001 | <0.001 | <0.001 | <0.001 | <0.001 | <0.001 |
| Hansen J test P-value | 0.471 | 0.857 | 0.513 | 0.800 | 0.572 | 0.805 | 0.567 | 0.836 |

All equations are estimated using a Fixed effects (FE) estimator. Time dummies are included in all specifications. Standard errors robust to heteroskedasticity and first-order serial correlation reported in parentheses. The dependent variable is log output (total sales). All company level variables have been instrumented with their own values at time t-1 and t-2. In the presence of heteroscedasticity, the Hansen J statistic is an appropriate test of the null hypothesis of instrument validity. The Kleibergen-Paap LM statistic tests the null hypothesis that the matrix of reduced-form coefficients in the first-stage regression is under-identified. ***, **, * significant at 1, 5 and 10%.

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[1] Bryonjolfsson and Hitt (2000) discuss how aggregation effects cause a downward bias in the evaluation of the returns to ICT. A similar downward bias could affect the assessment of the spillover effect. Haskel and Wallis (2010) discuss this issue in relation to lack of evidence of ICT and R&D spillovers in their study based on country-

[2] Griliches (1990) does not consider this type of spillovers as a proper knowledge spillover but rather as the result of an incorrect measure of capital equipment, materials and their prices.

[3] Stiroh's (2002) results could be explained by the fact that the study is carried out for manufacturing industries which are not the most intensive ICT-using industries. There is substantial evidence that the service sector is a heavy user of the new technology and it has played an important role in the US productivity resurgence (Inklaar et al. 2008). Focusing solely on manufacturing industries could results in a diminished effect for ICT spillovers.

[4] An exception to this pattern of results is Venturini (2011) where, using national data for 15 OECD countries, the author finds evidence of positive ICT spillovers, even when controlling for R&D capital.

[5] There is an extensive literature investigating the role of absorptive capacity in knowledge or technology transfers. See also Cohen and Levinthal (1989), Coe and Helpman (1995) and Yasar (2010).

[6] 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).

[7] A similar framework has been used by Los and Verspagen (2000) in the assessment of industry R&D spillovers.

[8] See Cincera and van Pottelsberghe (2001) for a summary of different spillover measures.

[9] Industry values for ICT capital are taken from the EU KLEMS data on the confidential permission of Mary O'Mahony. R&D capital at industry level is computed in a consistent way with company-level R&D stock.

[10] Companies that did not disclose any data for net sales, employment or net physical capital were excluded from the estimation, as were those companies displaying negative values. We also excluded companies for which the growth rate of these variables was more than 150% or lower than –150. 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. This criterion to remove outliers has been used recently in Aghion et al. (2005) and Bloom and Van Reenen (2002).

[11] Lee (2005) and Zhu and Jeon (2007) document that advanced telecom infrastructures have also enabled relevant technology transfers across countries.

[12] The business stealing effect (or product market rivalry) is estimated in Bloom et al. (2012) in relation to R&D spillovers for a sample of companies similar to the one used in this study.

[13] A typical concern working with microeconomic data in absence of company-level deflators is that the use of industry price indexes may be source of severe measurement errors that bias estimates. As suggested by Bloom et al. (2012, p. 20), one can check robustness of results by including the contemporaneous and the lagged values of industry output. When do this, estimates do change only marginally. Results available on request.

[14] For example, while the correlation between inter-industry ICT and inter industry R&D for the whole sample is around 0.6, in some industries it goes up to 0.9. Hence collinearity is an issue when trying to control for too many industry factors.