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ICT AS A GENERAL PURPOSE TECHNOLOGY: SPILLOVERS, ABSORPTIVE CAPACITY AND PRODUCTIVITY PERFORMANCE[*]

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Abstract

We analyse the impact of ICT spillovers on productivity 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. For inter-industry spillovers both contemporaneous and lagged effects are positive and significant. 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.

JEL codes: D24, D62, O33

Keywords: Productivity, ICT Spillovers, Absorptive Capacity, R&D

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1. 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, O'Mahony and Vecchi 2005, Venturini 2009). 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 and 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, Kretschmer 2012).

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. Some studies find significant effects (van Leeuwen and van der Wiel 2003, Severgnini 2011, Venturini 2011), while 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, Lee et al. 2013). This mixed set of results has lead researchers to doubt the importance of the GPT effects related to ICT (Draca et al. 2007).

The purpose of this paper is to re-examine the relationship between ICT spillovers and productivity considering four possible causes of such contrasting results. A first candidate is the level of aggregation of the data used in the analysis. 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] Second, we recognise that results can be greatly affected by the spillover proxy used in the analysis and that it is important to consider alternative measures to capture the complex way in which ICT spillovers operate throughout the economy.

Our third and fourth issue relates to the GPT nature of ICT. One of the characteristics of a GPT is its complementarity with existing or potential technology (Lipsey et al. 2005). This implies that a company's ability to absorb ICT spillovers is enhanced by its own investments in innovation activities, such as R&D and skills. In the 1990s the US experienced an R&D boom, particularly in high-tech sectors (Brown et al. 2009), and this could have complemented the adoption and diffusion of ICT. However, existing studies rarely take absorptive capacity into account. Finally, 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 adjustment period, 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).

The four issues discussed above (aggregation effects, spillover proxy, absorptive capacity and delayed effects) will drive our search for ICT spillovers. We adopt a micro perspective of analysis by using a panel of US firms, observed over the period 1991-2001. The focus on the 1990s allows us to look at the uptake of the digital economy, when firm

[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-level data.

heterogeneity is large and first-movers enjoy benefits which may cumulate over time. To capture the different channels of transmission of ICT spillovers we construct two ICT proxies. We first evaluate whether companies' productivity performance is affected by the total stock of ICT capital within each industry. This is a valid measure to assess the presence of intra-industry spillover effects whereby, for example, the activity of a microelectronics company benefits from the adoption of ICT within the whole electrical and optical equipment 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). This inter-industry effect is captured by means of a weighted ICT industry variable, where the weights capture the degree of companies' proximity, measured either in terms of intensity of transactions (using input-output coefficients of intermediate transactions) or technological proximity (using patent citation flows).

Throughout the analysis, we assess the presence of absorptive capacity using R&D information at the company level and interacting this variable with the ICT spillover proxies. Finally, we account for contemporaneous and lagged impacts of ICT spillovers on productivity by including various lags of both ICT and the interaction terms hence providing a test of the 'delayed hypothesis', which underlies the GPT framework (Brynjolfsson and Saunders 2009).

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. Our estimates suggest that it takes approximately 5 years for intra-industry spillovers to positively affect productivity performance. By contrast, inter-industry spillovers are positive and significant both in the short and in the long run. 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.

Our work also recognises the importance of correctly identifying both inputs elasticity and the spillover effects by using instrumental variable estimation. The identification of the ICT spillover effects is particularly challenging as these industry-level variables may pick up other factors not included in our model. In particular, the positive relationship between ICT at the industry level and companies' productivity could be the result of exogenous industry-specific technical change rather than a pure spillover. To discriminate between the two effects we adopt a two-stage procedure where, in the first step, we identify the ICT spillover variables exploiting variation on regulation level of telecom services' market; in the second step, we include the predicted values from this regression into the productivity function. We further control for the impact of industry-specific endogenous technological change by including industry measures of R&D in our specification. These control for the presence of knowledge spillovers from industry research to firm productivity performance. Our main results are robust to the implementation of this identification strategy and to additional robustness checks.

The following section presents an overview of the existing empirical evidence on the impact of spillovers on productivity (Section 2), discussing the main implications of ICT as a General Purpose Technology (GPT) and as a potential source of spillovers. Section 3 presents the model used in the empirical analysis and describes the data sources. Our econometric findings are shown and discussed in Section 4. Section 5 concludes the paper.

2. 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). 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 can be adopted to analyse spillovers from ICT. 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. This learning does not necessarily happen in isolation as firms learn from the experience of other firms (Aghion 2002).

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. 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 payments 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. Interactions with other firms are therefore the source of another type of spillover often associated with ICT, i.e. 'network externality', whereby the efficiency of products or services increases as they are adopted by more users (Atrostic and Nguyen 2005).

ICT may also generate 'pecuniary spillovers' as the combination of competition and innovation in the ICT-producing sector has allowed computer-using industries to benefit from lower costs (Jorgenson, 2001). These, however, cannot be considered as pure spillovers because they do not capture a transfer of knowledge but they result from an incorrect measure of capital equipment, materials and their prices (Griliches, 1990). The substantial productivity gains that firms would enjoy following a cost reduction are short lived with no implications for long-run growth (Branstetter 2001).

Although the possibilities for ICT spillovers are numerous and can affect companies' performance at different stages of the production process, so far the empirical analysis has provided only a weak evidence of such positive externalities, especially when relying on industry or national level data. Stiroh (2002) regresses TFP growth on ICT capital and other controls for 20 US manufacturing industries over the period 1984-1999. He finds no evidence of positive ICT capital spillovers, nor evidence of positive spillovers from individual components (computer capital and telecommunication capital).[2] Instead he finds that ICT had a negative impact on TFP growth. 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.[3] This possibility was recognized by Brynjolfsson and Hitt (2000) and, more recently, by Haskel and Wallis (2010) and 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. Similarly, Severgnini (2010) finds evidence of positive ICT spillovers in a sample of Italian manufacturing firms.

[2] 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).
[3] 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.

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).[4] The evidence on ICT spillovers, however, is still in its infancy and only a handful of studies present results which do not completely clarify the nature of the relationship between the two assets. For example, Hall at al. (2013) find that, although both R&D and ICT contribute to innovation and productivity, they do not complement each other. 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, Dranove et al. (2012) find some evidence of complementarity between IT and the availability of skills in local labour markets in US hospitals. Given that R&D can also proxy for high skilled employment, the lack of complementarity that emerges in studies covering a wide range of industries is puzzling.

The difficulty in identifying spillovers from ICT could also be a consequence of their lagged impact 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 organizational structure, business practices and customer relations (Brynjolfsson and Hitt 2003). This implies a substantial delay between initial investments and performance improvements, which also justifies a lagged ICT spillover effect[5].

[4] 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).

[5] 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

According to Basu et al. (2004) productivity improvements induced by ICT adoption at industry level may materialise with lags of 5 to 15 years, depending on the intensity of investment in complementary inputs. At the firm level, Brynjolfsson and Hitt (2003) analyze the lagged impact of ICT on TFP and they show that, in a first difference specification, ICT does not earn super-normal returns; 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.

3. 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 and are external to the decisions taken by any firm, so as to retain the perfectly competitive nature of the model. 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}), physical capital (K_{ijt}), and R&D capital (R_{ijt})[7]:

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

where i denotes firm, j industry and t time. The term A is the firm's total factor productivity and it is determined by an industry measure of ICT capital.

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.

[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 that we show below (see Griliches and Mairesse 1984 for a discussion).

[7] Since research expenses cannot be separated from capital and labour outlays, R&D capital is assumed to affect firm output via productivity spillovers. In fact, 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).

As discussed in the previous section, ICT facilitates knowledge transfers across firms and this can lead to important productivity spillovers. For example, a firm *i* operating in industry *j* can easily access information about its competitors, their range of products, prices and additional services, via an Internet search engine and use such information for its own production and/or marketing strategy. Also, firms may easily imitate best practices from first-move adopters, reaping important productivity benefits. This *within or intra-industry* spillover is captured in our analysis by the total stock of ICT at the industry level (defined as ICT_{jt}). ICT also facilitates knowledge acquisition about firms' suppliers (prices, type of products and services, innovative practices) as well as firms' clients (personalised offers based on client's previous purchases) which can feed into the firm's production function and lead to productivity gains. Hence, ICT may also be a source of *between or inter-industry* spillovers. Both sources of spillovers will be stronger the larger the number of firms adopting the new technology, hence our analysis implicitly captures the effect of network spillovers.

To trace inter-industry flows of spillovers we use industry series on ICT, weighted by input-output intermediate transactions' coefficients, denoted by $wICT_{jt}$ and constructed as follows[8]:

$$wICT_{jt} = \sum_{j=1}^{17} w_{jft} \times ICT_{ft} = \sum_{j=1}^{17} \frac{M_{jft}}{Y_{jft}} \times ICT_{ft} \tag{2}$$

with $f \neq j$ and t=1991, ..., 2001. ICT_j is the ICT capital stock in the industry *j* where company *i* is located. ICT_f is the value of the surrounding industries ($f \neq j$). 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,

[8] Several contributions claim that weighted measures of the pool of external knowledge are better spillover proxies as the weights capture the degree of 'closeness' between firms, expressed as 'technological' distance (Jaffe 1986), the degree of product market proximity (Bloom et al. 2013) or geographical distance (Lychagin et al. 2010). 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. The weighting technique adopted here accounts for linkages between suppliers and customers, as in Mun and Nadiri (2002). Alternative weighting schemes, based on inter-industry patent citations, are considered in Appendix 1.

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. Denoting the log of variables in lower case letters, and introducing the effect of the two spillover channels, our empirical specification can be written as (benchmark model):

$$y_{ijt} = a_i + \alpha l_{ijt} + \beta k_{ijt} + \gamma r_{ijt} + \chi_1 ict_{jt} + \chi_2 wict_{jt} + \sum_{t=1}^{10} \delta d_t + \varepsilon_{ijt} \qquad (3)$$

where a_i is a company specific intercept (fixed effect), which captures the time-invariant effect of other intangible factors (organizational inputs, management practices, etc.) that are not available from company accounts. The coefficients α and β are standard output elasticities to factor inputs, γ identifies productivity externalities related to firm R&D capital (excess returns), χ_1 captures externalities directly associated with *intra-industry* spillovers and χ_2 captures the effect of *inter-industry* knowledge transfers. Both ICT variables are normalized on industry employment in order to neutralize possible scale effects on firm performance and identify the average value of ICT per capital available to each worker in the sector (ICT_{jt}). 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. d_t are common time dummies (to be discussed below).

ICT diffusion enables companies to access a large pool of external knowledge; however, to make a productive use of this knowledge, companies need to be endowed with the relevant skills and competencies; in other words, the impact of the ICT spillovers may depend on companies' absorptive capacity. Following Griffith et al. (2004) we assume that the cumulative value of firms' investments in R&D acts not only as an input to the production process, but also as an indicator of the company's absorptive capacity; hence, we expand equation (3) to include the interaction between company's R&D capital and our two ICT spillover measures:

$$y_{ijt} = a_i + \alpha l_{ijt} + \beta k_{ijt} + \gamma r_{ijt} + \chi_1 ict_{jt} + \eta r_{ijt} * ict_{jt} + \chi_2 wict_{jt} + \rho r_{ijt} * wict_{jt} + \sum_{t=1}^{10} \delta d_t + \varepsilon_{ijt} \quad (4)$$

where η and ρ are the portion of ICT spillovers acquired by the firm through its knowledge base (i.e. its absorptive capacity). The total impact of *intra-industry* ICT spillovers is therefore given by $\chi_1 + \eta\ r_{ijt}$, evaluated at different points of the R&D distribution. Equation (4) models the possibilities that firms may benefit from ICT spillovers by means of their absorptive capacity (η>0, χ_1=0), directly without any R&D investments (η=0, χ_1>0), or more widely through both channels (η>0, χ_1>0). In the same way, we can calculate the total impact of *inter-industry spillovers*. As a result, the *overall* spillover effect from ICT will be given by the sum of the two types of spillovers.

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 1990, 1992, Vecchi 2000). One drawback of this methodology is that the externality index is the same for several companies in a given year and it may be functioning simply as a proxy for a set of time period dummies (Oulton 1996, Pesaran 2006). This requires time dummies to be included in all specifications so that any spillover effect will be net of other cyclical and/or exogenous components (d_t).

3.*1 Econometric issues*

Obtaining consistent estimates of the input elasticities in equations (3) and (4) requires us to address two key econometric issues: cross sectional heterogeneity and endogeneity. The former is addressed with the use of panel data methods (Fixed Effect estimator) and the inclusion of time dummies, as discussed above. The main cause of endogeneity in production function estimation arises from the fact that the error term contains unmeasured components that are unknown to the econometrician but known to the firm, and are therefore transmitted to the firm's choice regarding factors inputs (Griliches and Mairesse 1995, Eberhart and Helmers, 2010). This results in upward biased coefficients, particularly for those inputs that can be more easily adjusted following a productivity shock. Next to this 'transmission bias', measurement errors in the input variables lead to an 'attenuation bias' which produces a downward bias of the estimated elasticities. The use of panel data methods, by removing unobserved fixed effects, partially addresses these issues but it still leaves some simultaneity unaccounted for.[9] To address this problem we use a Generalised Method of Moments (GMM) estimator where lagged values of the endogenous regressors are used as instruments for firm-level variables, namely labour, capital and R&D, under the assumption that productivity shocks at time *t* are uncorrelated with input choices in previous periods. We limit the number of lags to three to avoid instrument proliferation and the associated upward bias in estimated coefficients (Roodman 2009). The validity of the instruments is assessed by the Kleibergen and Paap (2006) test of under-identification and the Hansen-J (1982) test of over-identifying restrictions. We also correct the covariance matrix for arbitrary heteroskedasticity and for the presence of first-order serial correlation.

The identification of the ICT spillover can also pose a challenge to our estimation. In fact, an industry measure of ICT could capture endogenous industry specific-technical change as well as technology diffusion, rather than pure (exogenous) spillovers. For example, when a new technology is introduced in a particular industry, a firm adopting this technology can experience an increase in productivity. This effect would be captured by our ICT proxies and erroneously interpreted as a spillover.

[9] Other sources of endogeneity are coefficient heterogeneity, which is 'imperfectly' addressed by focusing on narrowly defined industrial sectors, and a selection bias which results from firms entering and exiting the panel in any given period. We address these problems when carrying out additional robustness tests, described in Ssection 4.3.

To avoid this problem and to correctly identify the spillover effect, we follow a dual strategy. First, we introduce measures of R&D at the industry level so any spillover effect will be net of other industry-specific endogenous technological innovation. Additionally, this variable will control for R&D-based knowledge spillovers, whose effect could also be confounded with spillovers from ICT (Acharya and Basu 2010). To this end, similarly to ICT, we construct an intra-industry and an inter-industry measure of R&D capital. The latter is based on the same weighting scheme adopted to build the inter-industry ICT variable. Second, we follow Bloom et al. (2013) in implementing a two-stage instrumental variable approach, where in the first stage we project ICT on a set of instruments and, in the second stage, we replace actual ICT with its fitted values, re-constructing both the un-weighted ($\widehat{ICT}_{jt}$) and the weighted ICT spillover measures ($w\widehat{ICT}_{jt}$). Our first-step consists in regressing ICT capital per worker on the OECD index of regulation of the telecom service industry (*regtel*), and a set of industry and time dummies (a_j and d_t), as follows:

$$ict_{jt} = a_j + regtel_{jt} + \sum_{t=1}^{10} \delta d_t + \varepsilon_{jt} \qquad (5)$$

where *regtel* is the OECD index of regulation on telecom services (in logs), which ranges between 0 and 6, with higher values indicating stricter administrative barriers to competition (i.e. market entry, private ownership, etc.).[10]

For a variable to be considered a valid instrument it has to satisfy two conditions: the instrument must be relevant, i.e. correlated with the potentially endogenous variable, and it must be orthogonal to the error term. Our instrument choice relies on the fact that lower administrative barriers in the telecom sector would contribute to a larger supply of digital service inputs and therefore to an increasing demand for complementary assets, such as computers and other communication devices. The faster liberalisation of the US telecom market during the 1990s may have favoured the adoption of new digital technologies as these assets

[10] Equation (5) is estimated with the Newey-West estimator in order to control for serial correlation and arbitrary heteroskedasticity.

have been increasingly dependent on the provision of Internet services. This implies a strong correlation between our instrument and the stock of ICT at the industry level. At the same time, the regulation indicator results from a long-lasting political decision making process, which can be considered as predetermined with respect to firms' investment choices. Hence, we rule out the possibility that the ICT spillover variables capture the endogenous adoption of the new technology.

3.2. Data sources and descriptive statistics

We use US company accounts from the Compustat database for the period 1991-2001. Our analysis therefore covers the entire cycle of the New Economy growth, from the earlier phases of ICT uptake to the collapse of the ICT bubble in the stock market. 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).[11] 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

[11] 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).

are taken from the OECD I-O output table at benchmark years and are interpolated for intermediate observations. Data on telecom service regulation come from the OECD product market regulation dataset (Conway and Nicoletti, 2006).

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, *ICT*, 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 (*ICT* vs *wICT*), the cumulative value of intra-industry R&D sizeably exceeds inter-industry knowledge capital (*RD* vs *wRD*). 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 $92,400 per worker), followed by chemicals and business services. In the service industries we observe the highest levels of intra-industry ICT per worker (ICT_{jk}) while inter-industry ICT ($wICT_{jk}$) is higher in manufacturing industries due to their more intensive inter-industry intermediate transactions.

[Table 2 here]

4. Results

4.1 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, under the assumption that these variables are uncorrelated with other external sources of companies' productivity performance. We will relax this assumption in Section 4.2. 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. 2013) 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 (3). 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 opposite directions. 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.

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 product market rivalry (or 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. 2013)[12]. Later on in the paper we will discriminate between these two alternative interpretations (see Section 4.3).

[Table 3 here]

In Table 4 we present the estimation of our extended model which accounts for the role of firms' absorptive capacity. Our main hypothesis is that 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 (4). 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]

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

[12] The business stealing effect (or product market rivalry) is estimated in Bloom et al. (2013) in relation to R&D spillovers for a sample of companies similar to the one used in this study.

innovative effort and industry ICT capital (Columns 1-2). However, 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 interaction between company's R&D and inter-industry ICT affects the R&D coefficient in an inconsistent way. In fact, in column 2, own R&D is not statistically different from zero, while in column 3 it jumps to 0.229. This is likely to be the result of a collinearity problem between interaction terms and companies' R&D. 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 3.1, 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. 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 R&D distribution (over the 95th percentile), intra-industry spillovers were exactly compensated by a 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 for a typical US company.

4.2. Identification of the spillover effect

In this section we re-estimate equation (4) accounting for the possibility that our ICT spillover variables might capture the impact of industry specific endogenous technological change or R&D spillovers, following the methodology discussed in Section 3.1. Results are presented in Table 5. In column 1, we find a positive effect of intra-industry R&D capital, while the ICT spillover impacts on productivity are still strong and significant. In column 2 we introduce the inter-industry R&D variable but this generates an unexpected result, being its coefficient negative and strongly significant. This finding contrasts with the evidence of positive knowledge spillovers in US firms, documented in Los and Verspagen, (2000). 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.[13] In fact, the coefficient on inter-industry ICT becomes over twice as large as the coefficient reported in column 1 (0.458 versus 0.207).

In column 3 we conduct a further robustness check for the ICT spillover effect by including the total number of hours worked in our specification. This variable aims to control for changes in labour utilization over the business cycle, whose effect could be picked up by our spillover proxies. For example, Oliner et al. (2008) suggest that the resurgence in labour productivity in the 1990s could have been caused by normal cyclical dynamics.[14] The coefficient on the total number of hours worked is positive and statistically significant, confirming the cyclicality of productivity movements; however, its inclusion does not alter the pattern of our results.

In columns 4-6 we treat the spillover variables as endogenous and use the OECD index of regulation of the telecom sector as an instrument, next to time and industry dummies as discussed in Section 3.2. The coefficient on *regtel* in the first stage results is -0.94 and statistically significant at the 1% significance level. The F-test on the significance of excluded instrument is above the rule of the thumb value of 16 (Stock and Yogo 2005). The second stage coefficients are presented in the right-hand side of Table 5. Results regarding the ICT spillover

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[13] 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. However, it should be added that when we replicate this regression using patent citations-based weights, the coefficient of inter-industry R&D variable is no longer significant (unreported but available on request).

[14] See also Hall (1988) and Vecchi (2000).

effects are confirmed. The main difference compared to the first half of the table is that neither the intra-industry R&D variable nor the total number of hours worked are statistically significant. More importantly, results in Table 5 are not qualitatively different from those reported in Table 4; this means that our ICT industry variables are indeed capturing a true spillover effect and not, for example, the impact of other un-observed technological factors. The overall impact of ICT spillovers on productivity, computed using the coefficients in column (4), also confirms the results in Table 4: only companies at the higher end of the R&D distributions can offset the negative ICT intra industry spillover.

[Table 5 here]

In the reminder of the paper we will relax the assumption of endogenous ICT spillovers while investigating the 'delayed effects' hypothesis for industry ICT. To test this hypothesis we rely on the use of lagged values of the ICT proxies, which should mitigate any remaining endogeneity issues.

4.3 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 test the hypothesis of delayed spillover effects by controlling for the lagged impact of ICT spillovers on productivity. In the first three columns of Table 6 we consider up to

5 lags of the ICT spillovers and the interaction terms. In columns 4-6, we control for the impact of R&D at the industry level following the same lag structure.

[Table 6 here]

Results 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. These results are robust to the introduction of R&D at the industry level (columns 4-6), although the inter-industry effect is not longer statistically significant in the 5-year lag specification (column 6)[15]. The coefficient on the R&D spillover variable is statistically significant only at time *t-1*. Hence, our results suggest that the effect of industry R&D and ICT spillovers materialises with a different timing on companies' productivity. 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).

Our results show that all companies gain positive and significant productivity spillovers from industry ICT with a 5-year lag. The implied overall effect is not trivial: a 1% increase in industry ICT increases companies' productivity by approximately 0.1-0.2%. Furthermore, spillovers are not affected by companies' 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.

These results are robust to an array of robustness checks. First, we investigated whether alternative weighting schemes for the inter-industry ICT spillovers could affect our coefficient estimates. We constructed inter-industry measures based on the relative trade size of the recipient sector, as in Coe and Helpman (1995), and using information on inter-industry patent citations to trace potential spillover flows. The latter data control for the technology distance between pair of industries and therefore may better capture the ability of the firm in the receiving industry to assimilate technological externalities associated with the ICT usage in surrounding sectors. Results based on these alternative weighting schemes are still characterised by the same pattern discussed above (see Appendix A.1).

As additional sensitivity tests[16], we checked whether our coefficient estimates are somehow affected by attrition in the sample; for this reason, we ran our key specifications on a balanced sample of companies, and on a sample composed of firms with at least five years of data. We also removed from the sample large firms in terms of sales and R&D expenses (the top 5% performing companies) to check whether their presence might drive our results. Our main conclusions remained unchallenged. Finally, we sought to understand whether our results are driven by some specific industry patterns. We therefore ran our key specifications distinguishing between ICT producing and ICT using industries. In this case, albeit the contemporaneous effect of both types of ICT spillover was confirmed, their lagged impact was not statistically significant probably due to the very small sample size[17].

[15] We also considered a specification which includes inter-industry R&D instead of intra-industry. In this case the results are closer to those presented in columns (1) - (3), with a positive inter-industry ICT spillover at time *t-5*. Therefore, parameters reported on the right-hand side of the table have to be considered as lower bound values.

[16] These additional sensitivity tests are available upon request.

[17] Similar findings were obtained when distinguishing between R&D and non-R&D intensive, following the Eurostat classification.

5. Conclusions

This paper provides 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 construct two measures of ICT externalities and consider both contemporaneous and lagged spillover effects, with the aim of assessing the complex way in which ICT affects 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' costly 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 reverse causality, endogenous technological change, the presence 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

A.1. Additional robustness checks

This section reports some additional robustness checks for the key results of Table 6, based on alternative weighting schemes for the inter-industry ICT spillover variable. In our main set of results the weighting factor was given by the ratio between intermediate transactions among industries *j* and *f* (M_{jft}) and total intermediates' sales of the selling industry (Y_{ft}) - see equation (2). 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':

$$wICT_{jt}^{b} = \sum_{j=1}^{17} w_{jft}^{b} \times ICT_{ft} = \sum_{j=1}^{17} \frac{M_{jft}}{P_{jt}} \times ICT_{ft} \qquad \text{(A.1)}$$

Results based on this measure are presented in cols. (1) and (2) 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.2), the weighting factor (w_{jft}^{p}) 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}):

$$wICT_{jt}^{p} = \sum_{j=1}^{12} w_{jft}^{p} \times ICT_{ft} = \sum_{j=1}^{12} \frac{C_{jft}}{C_{ft}} \times ICT_{ft}. \qquad \text{(A.2)}$$

In equation (A.3) the weighting factor is scaled by the total (forward) citations received by industry *f* (C_{ft}):

$$wICT_{jt}^{p,b} = \sum_{j=1}^{12} w_{jft}^{p,b} \times ICT_{ft} = \sum_{j=1}^{12} \frac{C_{jft}}{C_{jt}} \times ICT_{ft}. \quad \text{(A.3)}$$

Equation (A.3) defines the inter-industry ICT spillover variable using weights reflecting the total amount of knowledge "released" by contiguous industries ($wICT_{jt}^{b}$). Equation (A.3) considers as a scale factor the total amount of knowledge "acquired" by the recipient industry $wICT_{jt}^{p,b}$. Results based on these patent-weighted measures of spillovers are presented in columns 3-6 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 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)						
ICT_{jt}	Intra-industry ICT capital (p.w.)	9,480	4.8	5.1	0.092	36.7
$wICT_{jt}$	Inter-industry ICT capital (p.w.)	9,480	3.9	3.3	0.494	18.2
RD_{jt}	Intra-industry R&D capital (p.w.)	9,480	39.5	43.1	0.006	112.5
wRD_{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)	ICT_{jk}	$wICT_{jk}$	RD_{jk}	wRD_{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 (α)	0.765***	0.783***	0.774***	0.790***
	(0.034)	(0.035)	(0.035)	(0.035)
Physical capital (β)	0.120***	0.109***	0.119***	0.110***
	(0.026)	(0.026)	(0.026)	(0.026)
R&D capital (γ)	0.125***	0.135***	0.111***	0.119***
	(0.020)	(0.021)	(0.021)	(0.021)
Industry level variables				
Intra-industry ICT (χ_1)		-0.378***		-0.330***
		(0.040)		(0.039)
Inter-industry ICT (χ_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 are reported in parentheses. The dependent variable is the log of output (total sales). All company level variables have been instrumented with their own values up to three-year lags. In the presence of heteroscedasticity, the Hansen J statistic is the 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 (α)	0.781***	0.772***	0.790***	0.788***
	(0.035)	(0.035)	(0.035)	(0.035)
Physical capital (β)	0.112***	0.123***	0.112***	0.114***
	(0.026)	(0.027)	(0.027)	(0.026)
R&D capital (γ)	0.111***	0.043	0.229**	0.098***
	(0.022)	(0.043)	(0.114)	(0.023)
Industry level variables and interactions				
Intra-industry ICT (χ_1)	-0.441***		-0.525***	-0.390***
	(0.044)		(0.15)	(0.043)
Firm R&D*intra-industry ICT (η_1)	0.014***		0.039*	0.0129***
	(0.004)		(0.020)	(0.004)
Inter-industry ICT (χ_2)		0.221***	0.287***	0.202***
		(0.040)	(0.074)	(0.034)
Firm R&D*inter-industry ICT (η_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	η_1*ln(RD)*	0.00	0.02	0.02	0.04	0.05	0.07	0.09	0.10	0.12
b	*Intra-industry* (χ_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* (χ_2)	0.20	0.20	0.20	0.20	0.20	0.20	0.20	0.20	0.20
c=- d	*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 are reported in parentheses. The dependent variable is the log of output (total sales). All company level variables have been instrumented with their own values up to three-year lags. In the presence of heteroscedasticity, the Hansen J statistic is the 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

Identification of the ICT Spillover

	(1)	(2)	(3)	(4)	(5)	(6)
	Exogenous ICT spillovers			*Endogenous ICT spillovers*		
Company level variables						
Employment (α)	0.793***	0.788***	0.783***	0.762***	0.743***	0.749***
	(0.039)	(0.035)	(0.035)	(0.045)	(0.040)	(0.041)
Physical capital (β)	0.114***	0.114***	0.116***	0.124***	0.133***	0.130***
	(0.030)	(0.026)	(0.027)	(0.034)	(0.030)	(0.030)
R&D capital (γ)	0.092***	0.095***	0.096***	0.106***	0.092***	0.098***
	(0.025)	(0.023)	(0.023)	(0.028)	(0.027)	(0.026)
Industry level variables and interactions						
Intra-industry ICT ($\chi 1$)	-0.494***	-0.329***	-0.428***	-0.436***	-0.618***	-0.522***
	(0.057)	(0.0475)	(0.044)	(0.100)	(0.112)	(0.107)
Firm R&D*intra-industry ICT (η_1)	0.014***	0.014***	0.013***	0.013**	0.015***	0.012**
	(0.005)	(0.004)	(0.004)	(0.005)	(0.005)	(0.005)
Inter-industry ICT (χ_2)	0.207***	0.458***	0.219***	0.196***	0.401***	0.217***
	(0.038)	(0.084)	(0.035)	(0.042)	(0.081)	(0.040)
Intra-industry R&D (ϕ_1)	0.046**			-0.002		
	(0.019)			(0.021)		
Inter-industry R&D (ϕ_2)		-0.302***			-0.216***	
		(0.084)			(0.079)	
Hours worked (ρ)			0.207**			-0.104
			(0.090)			(0.102)
					First-stage	
					Coef. -0.94	
					F-test 755.2	
Obs.	5,814	6,704	6,704	4,982	5,689	5,689
R-squared	0.743	0.762	0.762	0.708	0.725	0.724
No. of Firms	785	938	938	755	886	886
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	0.327	0.316	0.517	0.333	0.390

TOTAL ICT SPILLOVER EFFECT (ESTIMATES FROM COLUMN 4)

	Percentile	**1%**	**5%**	**10%**	**25%**	**50%**	**75%**	**90%**	**95%**	**99%**
	Ln(R&D)	0.60	1.52	2.10	3.28	4.40	5.50	6.89	7.96	9.24
a	η_1*ln(R&D)*	0.01	0.02	0.03	0.04	0.06	0.07	0.09	0.10	0.12
b	*Intra-industry* (χ_1)	-0.436	-0.44	-0.44	-0.44	-0.44	-0.44	-0.44	-0.44	-0.44
c=a+b	*Total Intra-industry*	-0.43	-0.42	-0.41	-0.39	-0.38	-0.36	-0.35	-0.33	-0.32
d	*Inter industry* (χ_2)	0.20	0.20	0.20	0.20	0.20	0.20	0.20	0.20	0.20
c=- d	*P-value*	[0.01]	[0.02]	[0.02]	[0.03]	[0.04]	[0.06]	[0.10]	[0.14]	[0.21]

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 are reported in parentheses. The dependent variable is the log of output (total sales). All company level variables have been instrumented with their own values up to three-year lags. In the presence of heteroscedasticity, the Hansen J statistic is the 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

Lagged ICT Spillovers and Companies' Productivity Performance

	(1)	(2)	(3)	(4)	(5)	(6)
	1-year lag	*3-year lag*	*5-year lag*	*1-year lag*	*3-year lag*	*5-year lag*
Company level variables						
Employment (α)	0.783***	0.780***	0.771***	0.793***	0.802***	0.771***
	(0.035)	(0.043)	(0.067)	(0.039)	(0.048)	(0.073)
Physical capital (β)	0.120***	0.110***	0.095**	0.117***	0.100***	0.089*
	(0.026)	(0.031)	(0.047)	(0.030)	(0.035)	(0.052)
R&D capital (γ)	0.094***	0.115***	0.115***	0.090***	0.123***	0.139***
	(0.022)	(0.024)	(0.034)	(0.025)	(0.026)	(0.035)
Industry level variables and interactions						
Intra-industry ICT ($\chi 1$)	-0.415***	-0.196***	0.182**	-0.468***	-0.153**	0.158*
	(0.046)	(0.060)	(0.088)	(0.059)	(0.068)	(0.096)
Firm R&D*intra-industry ICT (η_1)	0.016***	0.014***	0.003	0.017***	0.015***	-0.004
	(0.004)	(0.005)	(0.008)	(0.005)	(0.005)	(0.008)
Inter-industry ICT (χ_2)	0.192***	0.230***	0.161***	0.173***	0.149***	0.075
	(0.032)	(0.036)	(0.043)	(0.036)	(0.041)	(0.047)
Intra-industry R&D (ϕ_1)				0.036**	-0.011	-0.043
				(0.018)	(0.021)	(0.034)
Obs.	6,704	5,893	4,049	5,814	5,128	3,585
R-squared	0.761	0.727	0.638	0.743	0.706	0.627
No. of Firms	938	915	808	785	770	703
Kleibergen-Paap LM test P-value	<0.001	<0.001	<0.001	<0.001	<0.001	<0.001
Hansen J test P-value	0.279	0.163	0.612	0.405	0.396	0.636

All equations are estimated using a GMM Fixed effects estimator. Time dummies are included in all specifications. Standard errors are robust to heteroskedasticity and first-order serial correlation are reported in parentheses. The dependent variable is the log of output (total sales). All company level variables have been instrumented with their own values up to three-year lags. In the pressence of heteroskedasticity the Hansen J statistic is the 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 intermediate purchases (A.1)		*Manufacturing* Total backward patent citations scaled on cited industry (A.2)		*Manufacturing* Total backward patent citations scaled on citing industry (A.3)	
	(1)	(2)	(3)	(4)	(5)	(6)
	Contempo-raneous	*5-year lag*	*Contempo-raneous*	*5-year lag*	*Contempo-raneous*	*5-year lag*
Company level variables						
Employment (α)	0.787***	0.770***	0.785***	0.768***	0.787***	0.769***
	(0.039)	(0.073)	(0.040)	(0.073)	(0.040)	(0.073)
Physical capital (β)	0.110***	0.087*	0.117***	0.088*	0.118***	0.088*
	(0.030)	(0.052)	(0.030)	(0.053)	(0.030)	(0.053)
R&D capital (γ)	0.111***	0.145***	0.107***	0.146***	0.089***	0.142***
	(0.025)	(0.035)	(0.025)	(0.036)	(0.025)	(0.036)
Industry level variables and interactions						
Intra-industry ICT ($\chi 1$)	-0.403***	0.169*	-0.379***	0.170*	-0.247***	0.175*
	(0.057)	(0.096)	(0.064)	(0.097)	(0.062)	(0.097)
Firm R&D*intra-industry ICT (η_1)	0.012**	0.004	0.014***	0.006	0.016***	0.005
	(0.005)	(0.008)	(0.005)	(0.008)	(0.005)	(0.008)
Inter-industry ICT (χ_2)	0.507***	0.051	0.434***	0.360***	0.380***	0.183***
	(0.105)	(0.107)	(0.123)	(0.116)	(0.052)	(0.044)
Intra-industry R&D (ϕ_1)	0.034	-0.052	0.077**	-0.051	0.0703**	-0.086*
	(0.022)	(0.034)	(0.033)	(0.042)	(0.032)	(0.046)
Obs.	6,704	4,049	5,680	3,517	5,680	3,517
R-squared	0.761	0.637	0.743	0.630	0.745	0.630
No. of Firms	938	808	761	688	761	688
Kleibergen-Paap LM test P-value	<0.001	<0.001	<0.001	<0.001	<0.001	<0.001
Hansen J test P-value	0.496	0.595	0.538	0.535	0.539	0.586

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 are reported in parentheses. The dependent variable is the log of output (total sales). All company level variables have been instrumented with their own values up to three-year lags. In the presence of heteroscedasticity, the Hansen J statistic is the 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%.