# Modelling the joint impact of R&D and ICT on productivity: A frontier analysis approach


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**Abstract**

This study explores the channels through which technological investments affect productivity performance of industrialized economies. Using a Stochastic Frontier Model (SFM) we estimate the productivity effects of R&D and ICT for a large sample of OECD industries between 1973 and 2007, identifying four channels of transmission: input accumulation, technological change, technical efficiency and spillovers. Our results show that ICT has been particularly effective in reducing production inefficiency and in generating inter-industry spillovers, while R&D has raised the rate of technical change and favoured knowledge spillovers within sectors. We also quantify the contribution of technological investments to output and total factor productivity growth documenting that R&D and ICT accounted for almost 95% of productivity growth in the OECD area.



Keywords**:** Research & Development; Information and Communication Technology; Productivity; Stochastic Frontier Models

JEL classification: O14, O32, O47

Acknowledgments: We are particularly grateful to Ana Rincon for providing part of the data used in the analysis. We also gratefully acknowledge the valuable comments by two reviewers. Comments from Michael Polder, and participants at conferences in Valencia (XX Encuentros de Economía Aplicada, June 2017), Mannheim (15th ZEW Conference, June 2017) and London (EWEPA conference 2017) are greatly appreciated. The usual disclaimer applies. Fabio Pieri acknowledges financial support from the Italian Ministry of Education, Universities and Research (FFABR 2017) and the Spanish Ministry of Science and Innovation (Project MINECO/FEDER ECO2015-68057-R).

## 1. Introduction

What do we know about the drivers of productivity? What are the channels through which innovative investments translate into better productivity performance? The economic growth literature still debates which factors produce long-lasting effects on productivity and explain cross-country productivity differentials (Madsen, 2008; Cette et al., 2016). The latest theories of endogenous growth highlight the importance of innovation activities in raising the rate of productivity growth, and hence living standards, in the long run (Aghion and Howitt, 1998; Dinopoulos and Thompson, 1998). In the empirical literature, innovative activities, typically proxied by investments in Research and Development (R&D), have long played a major role in boosting productivity performance at the country, industry and firm level (Griliches, 1979 1988; Patel and Soete, 1988; Guellec and Van Pottelsberghe, 2004; O'Mahony and Vecchi, 2009). Investments in R&D increase a country's competitive advantage, promote the international transfer of technological competences and intensify market competition, hence contributing to the growth of the so-called knowledge economy (Archibugi and Coco, 2005).

Since the mid-1990s, research has also focused on Information and Communication Technologies (ICT) and various contributions have shown that these assets are another important source of productivity growth in industrialized countries (O'Mahony and Vecchi, 2009; Venturini, 2009). ICT is often regarded as the main infrastructure of the knowledge (R&D-based) economy. However, the literature seldom considers its role next to the role of R&D (Polder et al., 2017). Exceptions include Hall et al. (2013) and Venturini (2015), who find that both ICT and R&D have positive but independent effects on Total Factor Productivity (TFP). Conversely, Corrado et al. (2017) document the presence of complementarities between ICT and intangible capital, which includes R&D and other innovative activities. Therefore, the empirical analysis so far does not provide a clear indication of the joint role of R&D and ICT or the different channels through which they affect productivity performance. The main objective of the present paper is to fill this important gap in the literature by investigating the productivity effects of both R&D and ICT and accounting for the possible ways in which these factors operate.

Thus far, the literature has analysed two main *channels* through which R&D and ICT can affect performance: *first*, an input accumulation channel, which focuses on the importance of capital deepening and on the productivity-enhancing effect of investments in knowledge assets. *Second*, a spillover channel, which recognises the possibility that technological investments promote the diffusion of knowledge across firms, both within the country and internationally (Coe and Helpman, 1995). The empirical evidence strongly supports the role of R&D as a factor of production and its ability to generate spillovers (Ugur et al., 2016). As for ICT, the evidence initially understated the extent of the input accumulation channel (Gordon, 2000), but a second wave of studies has documented that ICT is a significant driver of productivity growth (O'Mahony and Vecchi, 2005; Kretschmer, 2012).[1] The evaluation of the spillover potential for ICT has been more challenging. Stiroh (2002a) documents the absence of a relationship between ICT and TFP for the US, whilst Haskel and Wallis (2013) and Inklaar et al. (2008) provide similar evidence for European countries. Firm-level analysis is more supportive of the role of ICT spillovers, but contributions are still limited to single-country studies (Brynjolfsson and Hitt, 2003; Tambe and Hitt, 2014; Marsh et al. 2017).

A typical feature of this literature is the assumption that factor inputs are fully utilized and that there is no slack in production, i.e. all economic units are fully efficient (Greene, 2008). This assumption hides a potential *third* way in which R&D and ICT affect productivity, namely via their impact on technical efficiency, defined as the optimal combination of inputs to produce a given level of output. The evidence on the impact of R&D and ICT on production efficiency is sparse. Kneller and Stevens (2006) show that R&D investments affect the rate of technical change (i.e., they shift the production frontier outward) but they leave technical efficiency unchanged (i.e., they do not reduce the gap with the frontier). Bos et al. (2013) illustrate that R&D contributes to higher efficiency levels

[1] A recent contribution by Polák (2017) shows that the productivity effect of ICT may be lower than estimated in the post-1990s literature.

in mature industries, while it decreases efficiency in young industries. As for ICT, the General-Purpose Technology (GPT) literature has emphasised the link between new technologies and organizational changes (Jovanovic and Rousseau, 2005; Bresnahan and Trajtenberg, 1995). In fact, ICT has created opportunities for gathering and sharing information, both within and outside the firm, reducing administrative costs and improving supply chain management (Rowlatt, 2001; Criscuolo and Waldron, 2003). Hence, it is reasonable to assume that these developments contribute to a more efficient use of factor inputs within the production process. However, only a handful of papers have provided evidence in this respect. Becchetti et al. (2003) and Castiglione (2012) show that ICT investments reduce inefficiency in Italian firms. Papaioannou and Dimelis (2017) find a similar result at industry level but show that the effect of ICT is weaker in high-tech sectors. Using a cross-sectional sample of Italian companies, Bonanno (2016) relates both R&D and ICT investments to production efficiency, finding a positive effect for both technological assets.

Potentially, there is also a *fourth* channel of impact for R&D and ICT. These investments may expand the set of productive possibilities by enhancing the rate of technical change. Since the seminal work by Solow (1960), scholars have recognised that technical change may not be neutral but specific to firms' investments in new vintages of capital goods that embody the latest technologies (so-called investment-specific technical change). For example, Greenwood et al. (1997) illustrate that, in the US, the largest proportion of output growth is due to technical change embodied in machinery and equipment. Samaniego (2007) extends this analysis to investments in knowledge assets, finding that R&D-driven technical change is the main determinant of output growth. Venturini (2007) and Martínez et al. (2010) model the effect of ICT - specific technical change in promoting productivity growth in modern economies.

This paper investigates the impact of R&D and ICT on productivity performance, using a large panel data set covering fourteen countries and nineteen industries for the period between 1973 and 2007. Our analysis accounts for the four channels discussed above - input accumulation, spillovers, technical efficiency and technical change – within the same analytical framework. This relies on a

Stochastic Frontier Model (SFM), which allows the joint estimation of the different channels, as well as the quantification of their contribution to productivity growth. Throughout the analysis we control for cross-sectional dependence, which may be induced by increasing globalization and multilateral interconnection through historic, geographic and trade relations (Mastromarco et al., 2016; Eberhardt et al., 2013).

Our results show that R&D and ICT increase productivity levels through different transmission mechanisms. R&D drives productivity through all the proposed routes, whilst ICT operates via investment-specific technical change and efficiency before 1995 and input accumulation after 1995. Our analysis provides evidence of important spillover effects associated with both R&D and ICT, and supports the presence of complementarities between R&D and ICT in reducing inefficiencies in production. In addition, we document that the nature of the efficiency impact of R&D changes with the technology intensity of production. Specifically, R&D investments have detrimental effects on efficiency in high-tech but positive effects in low-tech industries. Conversely, ICT raises efficiency levels in all sectors. Finally, we quantify that R&D and ICT investment contributed 95% of TFP growth in OECD countries, a result that unequivocally points to a key role for these technological assets in the knowledge economies.

This study relates to the literature on the drivers of productivity and the key sources of competitiveness in the global economy, offering important insights into the debate on the secular stagnation of productivity growth (Gordon, 2016; Jorgenson et al., 2016). We also contribute to those studies investigating whether returns to innovation change with technological opportunities and appropriability conditions (Terleckyj, 1974; Nelson, 1988; Ngai and Samaniego, 2011). Finally, our results add to the new literature on the impact of intangible assets on TFP growth, by detailing the transmission mechanisms via technical change and technical efficiency that have been largely unexplored to date (Corrado et al., 2017; Niebel et al., 2017). Hence, our analysis sheds light on how investments in intangibles, which include both R&D and computerized software among others, translate into greater productivity outcomes. Identifying the drivers of productivity growth and the different transmission mechanisms can be crucial for the design of policies aimed at improving growth performance (OECD, 2015).

The structure of the paper is the following. Section 2 draws the theoretical underpinnings of the link between R&D and ICT investments and productivity. Section 3 introduces our analytical framework, showing how ICT and R&D influence productivity performance within a SFM framework. Section 4 describes the data and presents a descriptive analysis. Section 5 presents the main results and discusses robustness tests. Section 6 quantifies the contribution of R&D and ICT to productivity growth and offers some insights for policymaking. Finally, Section 7 concludes the paper.

## 2. Background

The positive relationship between innovation and productivity performance is indisputable. Since the seminal works by Griliches (1958) and Evenson (1968), investments in R&D have been considered among the main drivers of TFP growth, i.e. the increase in output which is not accounted for by changes in labour and capital inputs. Many papers have concluded that R&D-based innovation yields positive effects on the productivity of innovators as well as on that of "related" firms/industries/countries in the form of knowledge spillovers (Mairesse and Sassenou, 1991; Sveikauskas, 2007; Ugur et al., 2016). R&D has also been considered one of the sources of absorptive capacity, which refers to the ability of companies to effectively benefit from the new knowledge created in neighbouring firms or industries (Griffith et al., 2004; Bos et al., 2010; O'Mahony and Vecchi, 2009).

Since the mid-1990s, the debate on innovation and productivity has concentrated on the new paradigm of the knowledge-based economy, which focuses on knowledge generating activities as the main source of firms' competitive advantage. The defining features of the knowledge-based economy are: i) a more systematic exploitation of knowledge by profit seeking companies; ii) greater transfers of material and immaterial resources driven by ICT advances; iii) an accelerated pace of global competition (Archibugi and Coco, 2005). This paradigm fully acknowledges the role of both R&D and ICT in promoting the development of the knowledge economy, which in turns leads to an acceleration in productivity growth. Since 1995 productivity has accelerated in the US, the country at the forefront of the digital revolution, with European countries expected to follow, albeit with a lag due to lower investments in R&D and later adoption of ICT (Daveri, 2002).

The literature has also highlighted the presence of heterogeneous returns to R&D and ICT across different industries. Firms operating in technologically advanced (high-tech) productions are able to reap larger benefits from their R&D investments (Griliches and Lichtenberg, 1984; Kumbhakar et al., 2012; Sterlacchini and Venturini, 2014). This is due to either different technological opportunities and appropriability conditions (Levin et al., 1985; Jaffe, 1986); different demand conditions, level and cumulativeness of knowledge (Malerba and Orsenigo, 1996; Malerba, 2002); or the different technological environments in which innovative activities take place (Castellacci and Zheng, 2010). As for ICT, the literature shows that the impact of ICT investments on productivity growth is higher in sectors that produce or intensively use ICT capital goods (Stiroh, 2002b). These include very diverse industries such as ICT manufacturing and market services (Timmer and Van Ark, 2005; Inklaar et al., 2008) Hence, accounting for industry heterogeneity is crucial to understand the impact of innovative activities on productivity performance.

The literature has also focused on how new digital technologies promote innovative activities, hence putting forward the concept of complementarities between R&D and ICT (Ding et al., 2010). For example, Kleis et al. (2012) estimate that a 10% increase in ICT investment raises patenting returns of R&D by 1.7%, and that this effect has become stronger from the midst of the 1990s. Other contributions have looked at whether ICT magnifies returns to R&D and other intangibles investments (Chen et al., 2016; Corrado et al., 2017), facilitates knowledge spillovers (Zhu and Jeon, 2007) or promotes international R&D collaborations (Forman and van Zeebroek, 2012). However, the evidence on the role of ICT, next to that one of R&D, on productivity performance is still weak (Polder et al., 2017).

In the reminder of the paper, we address these important issues by including both R&D and ICT in our analysis of productivity and allowing for differences in their impact over time and across different types of industries. Our methodological framework accounts for different channels through which R&D and ICT operate, which are discussed in detail in the next section.

## 3. Analytical framework

### *3.1 A stochastic frontier production model*

We base our analysis on a frontier production function, which identifies the maximum output achievable, given the current status of production technology and the amount of available inputs[2]. In a panel data setting, the maximum output ($Y^*_{ijt}$) is the boundary level of a common production set and, hence, we can express the frontier as (Bos et al., 2010):

$$Y^*_{ijt} = f\left(X_{ijt}; \beta\right)\exp(v_{ijt}) \tag{1}$$

where $i$'s denote industries, $j$'s countries, and $t$'s time observations. $X_{ijt}$ identifies the set of production inputs, $\beta$ is the vector of technology parameters, whilst $v_{ijt}$ is an i.i.d. error term. The disturbance term is distributed as a $N(0, \sigma_v^2)$, capturing the effect of unobserved random shocks and measurement errors. Industries that lie below the frontier are characterised by production inefficiency. Therefore, we can define their output as the frontier output multiplied by an inefficiency term measuring the deviation (gap) from the frontier, $Y_{ijt}/Y^*_{ijt} = \exp\left(-u_{ijt}\right)$:

$$Y_{ijt} = Y^*_{ijt}\exp\left(-u_{ijt}\right) = f\left(X_{ijt}; \beta\right)\exp\left(v_{ijt}\right)\exp\left(-u_{ijt}\right). \tag{2}$$

We assume that the inefficiency term is positive ($u_{it} \geq 0$), identically distributed as a half-normal and independent from the noise term, $v_{ijt}$. These distributional assumptions are necessary to identify technical inefficiency separately from the standard noise (Kumbhakar and Lovell, 2000). In

[2] Seminal contributions to stochastic frontier models are Aigner et al. (1977) and Meeusen and van den Broeck (1977). See Greene (2008) for a comprehensive review.

the light of these hypotheses, the inefficiency term ranges between 0 and $+\infty$, taking the value of 0 for the fully efficient (frontier) industries.

The model described in eq. (2) has three key properties (Kneller and Stevens, 2006; Bos et al., 2013). First, the frontier is determined empirically at each point in time by a set of industry-country pairs.[3] Second, the frontier is stochastic, due to the inclusion of $v_{ijt}$, and hence is suitable for statistical inference and hypothesis testing. This makes our model different from the non-parametric approach of analysis employed by Färe et al. (1994), Kumar and Russell (2002), and others. Third, by using the SFM, we can identify contributions (and relative importance) of technical change and efficiency change to TFP growth.

We specify the frontier as a translog production function, taken in logs (logged variables in lower case letters), as follows:

$$y_{ijt} = \sum_{n} \beta_n \cdot (x_{nijt}) + \frac{1}{2}\sum_{n}\sum_{p}\beta_{np} \cdot (x_{nijt}x_{pijt}) + tfp_{ijt} + \alpha_i + \mu_j + v_{ijt} \qquad (3)$$

We assume that output production depends on three inputs, namely labour, ICT capital, and non-ICT capital ($n, p = L, ICT, K$) and the level of TFP. Our specification includes two sets of intercepts, $\alpha_i$ and $\mu_j$, to control for unobserved (time-invariant) heterogeneity at industry and country level.

Next, we model TFP levels as a combination of three components (eq. 4). First, we assume that productivity performance depends on cumulative investments in R&D within the industry as proxied by R&D capital stock, $R\&D_{ijt}$ (Griliches, 1980). This term would capture within-industry R&D spillovers, i.e. excess returns to R&D associated with labour and capital inputs used in research departments. Second, TFP evolves as a result of technical change. This can be neutral, as captured by the time trend $t$, or investment-specific as measured by the interaction between $R\&D_{ijt}$ or $ICT_{ijt}$ and

[3] In essence, we compare each industry with the set of industry-country pairs lying on the frontier. Conversely, the mainstream productivity literature defines the frontier as the (unique) industry-country pair with the highest TFP level (see Griffith et al., 2004; Minniti and Venturini, 2017 among others).

the time trend itself ($t \cdot R\&D_{ijt}$ and $t \cdot ICT_{ijt}$). Lastly, a third component accounts for the distance from the production boundary, i.e. the inefficiency term ($u_{ijt}$).

$$tfp_{ijt} = \underbrace{\theta \cdot \ln R\&D_{ijt}}_{R\&D\ spillovers} + \underbrace{(\rho_0 \cdot t + \rho_1 \cdot t \cdot ICT_{ijt} + \rho_2 \cdot t \cdot R\&D_{ijt})}_{technical\ change} - \underbrace{u_{ijt}}_{inefficiency} \quad (4)$$

We obtain the production frontier by plugging eq. (4) into eq. (3). In our framework, $R\&D_{ijt}$ and $ICT_{ijt}$ may affect efficiency via the variance of the distribution of the inefficiency term (Caudill and Ford, 1993):[4]

$$\log(\sigma^2_{u,ijt}) = \delta_0 + \delta_1 \cdot \ln ICT_{ijt} + \delta_2 \cdot \ln R\&D_{ijt} \quad (5)$$

In summary, this setting extends the main framework used in earlier works by allowing ICT to impact on TFP via the investment-specific route ($\beta_{ict}$ in. eq. 1), via investment-specific technical change ($\rho_1$ in eq. 4) and via the efficiency route ($\delta_1$ in eq. 5). At the same time, we also account for the multifaceted effect of R&D, which operates via a within-industry spillover impact on TFP ($\theta$ in eq. 4), an effect on investment-specific technical change ($\rho_2$ in eq. 4) and on efficiency ($\delta_2$ in eq. 5).

### *3.2 Estimation method and a preliminary test on the adequacy of the Stochastic Frontier Model*

We jointly estimate the parameters of the production frontier, ($\boldsymbol{\beta}, \theta, \boldsymbol{\rho}, \alpha_i, \mu_j$), and of the inefficiency equation, ($\boldsymbol{\delta}$), via maximum likelihood, in a one-step procedure (Wang and Schmidt, 2002).

A convenient parametrization to identify the impact of the efficiency determinants is to set ${\sigma_{ijt}}^2 = (\sigma^2_{u_{ijt}} + \sigma^2_v)$ and $\lambda = \sigma_{u_{ijt}}/\sigma_v$ (Greene, 2008, p. 117). λ measures the relative contribution of the two components of the error term, $v_{ijt}$ and $u_{ijt}$. If this ratio is not statistically different from zero, there is no inefficiency in the data and hence the SFM is not suitable for our analysis. This

[4] Our analytical framework has the advantage of (i) incorporating exogenous influences on efficiency and (ii) correcting for heteroskedasticity in the SFM. Uncontrolled heteroskedasticity in the inefficiency term would bias estimates of technology parameters (see Kumbhakar and Lovell, 2000, pp. 272-3).

condition can be checked by means of a likelihood ratio test. Our data strongly support the adoption of a frontier model (see raw 3, Table A.2 in the Appendix).[5]

Recent studies using stochastic frontier models have addressed the issue of the presence of unknown common factors creating strong dependency across panel units (Mastromarco et al., 2016). Examples of these unobserved factors include global shocks, such as financial factors or knowledge spillovers (Chudik and Fratzscher, 2011; Eberhardt et al., 2013). If unobserved factors are uncorrelated with the main regressors, failing to account for these effects leads to inefficient estimates. If such un-accounted factors are correlated with the regressors, estimates can be biased. Here, to get consistent estimates, we adopt the Pooled Common Correlated Effects (CCE) estimator, following Pesaran (2006). We therefore approximate the effect of unobserved common factors with the cross-sectional averages of dependent and independent variables, and (initially) assume that such effects do not vary across the units of our panel sample.

## 4. Data and descriptive analysis

Our analysis uses industry-level data, extracted from the EU KLEMS database (O'Mahony and Timmer 2009) and the OECD ANBERD database. The sample includes fourteen OECD countries (Austria, Belgium, Denmark, Germany, Spain, Finland, France, Ireland, Italy, Japan, Netherlands, Sweden, UK and US). For each country, data are available for nineteen market industries.[6] The final sample is unbalanced and covers the period from 1973 and 2007. Therefore, our analysis will provide an overall picture of industry performance in the pre-financial crisis period.

[5] To validate our framework of analysis, we also carried out a battery of tests on the functional form, namely a translog vs a Cobb-Douglas production function. The likelihood ratio test on the null hypothesis that the parameters of second-order terms are jointly insignificant is largely rejected (raw 1, Table A.2), validating our choice of using former specification. Notice that we also rejected the hypothesis of constant returns to scale (raw 2, Table A.2).

[6] Industry list (ISIC 3, Rev. 1 codes): Food and Beverages (15t16), Textile and Leather (17t19), Wood & Cork (20), Pulp, Paper and Printing (21t22), Coke, refined petroleum and nuclear fuel (23), Chemicals (24), Rubber and Plastic (25), Other non-metallic minerals (26), Basic metals, fabricated metal products (27t28), Machinery NEC (29), Electrical Equipment (30t33), Transport Equipment (34t35), Manufacturing NEC (36t37), Transport and Storage (60t63), Post and Telecommunication (64), Business Services (71t74), Wholesale and Retail (50t52), Financial Intermediation (65t67), Other Community and Social Services (90t93).

We measure industry output in terms of value added. Labour input is the number of hours worked. We distinguish between two components of fixed capitals, ICT assets (computers, communication equipment and software) and non-ICT assets (structures, transport equipment and other equipment). These stocks are built from annual investment flows by means of the perpetual inventory method and adopting an asset-specific rate of geometric depreciation. As a measure of R&D input, we use the cumulative value of industry research expenses; we construct this stock with the same method adopted for physical assets but imposing a standard depreciation rate of 15%. We express all monetary variables at constant prices and in purchasing power parities of 1997 (PPP) based on the industry output PPP deflator developed by Inklaar and Timmer (2008).

**Figure 1. Dynamics of R&D and ICT stock (1973-2007)**

**Fig. 2a.** Evolution of the average R&D stock per employee

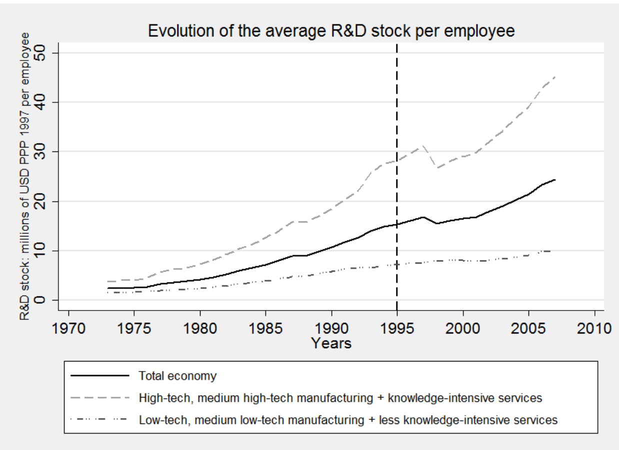


**Fig. 1b.** Evolution of the average ICT stock per employee

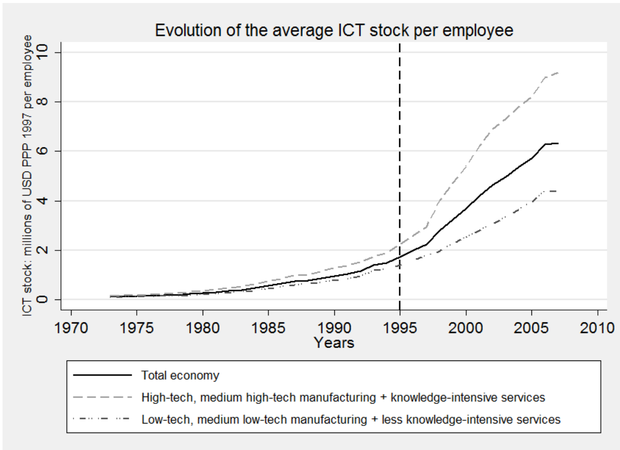


Fig. 1 plots average R&D (Fig. 1a) and ICT (Fig. 1b) stocks over the 1973 - 2007 period. For comparison purposes, we express these stocks in per worker terms and compute them as simple cross-country, cross-industry averages. We present the average for the total economy and for high-tech versus low-tech sectors. The first group includes high-tech, medium high-tech manufacturing and knowledge-intensive services industries, whilst the second one includes low-tech, medium-low tech manufacturing and less knowledge-intensive services industries (Eurostat classification).[7]

[7] http://ec.europa.eu/eurostat/cache/metadata/Annexes/htec_esms_an2.pdf

The figure illustrates the marked increase in the cumulative value of technological investments around the mid-1990s and the striking difference between the two industry groupings for both R&D and ICT. In high-tech industries, the accumulation of R&D stock accelerated between 1992 and 1997, and after a brief slowdown, this trend speeded up again in the late 1990s. The increase in ICT capital per worker was extraordinary since 1995, with important differences between industry types, which are however less pronounced compared to R&D. Jorgenson (2001) documents that the rapid diffusion of the new digital technologies was induced by the dramatic fall in ICT prices that originated in the stellar improvement in semiconductor products, resulting from an intensified competition and research activity in the semiconductor market.

Table 1 reports the average value of the variables used in the analysis (taken in absolute terms), for the overall time interval and distinguishing between the pre- and post-1995 period. On average, ICT stock amounted to one third of R&D stock (1,765 vs 5,823 of millions of USD) but grew much faster throughout the overall period between 1973 and 2007. Moreover, ICT capital accumulation accelerated by a factor of 2.4 since the mid-1990s (last column, Table 1).[8]

**Table 1. Summary statistics**

| | 1973-2007 | 1973-1995 | 1995-2007 | Log-difference pre- and post-1995 |
|---|---|---|---|---|
| Value added | 28,400 | 19,827 | 38,418 | 0.66 |
| Total hours worked | 1,072 | 987 | 1,172 | 0.17 |
| Non-ICT capital stock | 10,543 | 8,070 | 13,433 | 0.51 |
| ICT capital stock | 1,765 | 309 | 3,466 | 2.42 |
| R&D stock | 5,823 | 4,173 | 7,751 | 0.62 |

Note: monetary variables are expressed in millions of USD PPP 1997; hours worked are expressed in thousands.

[8] Estimating an autoregressive model of ICT capital accumulation we find a statistically significant acceleration (structural break) after 1995, in line with the evidence provided by Stiroh (2002b) for the US (results available upon request).

## 5. Empirical Results

### *5.1 Baseline estimates*

Table 2 presents our first set of results. We divide the table into three panels. Panel A presents the estimation of the production function.[9] Panel B reports the estimated impact of the inefficiency determinants, whereas panel C displays estimates of the standard deviation of the normally distributed error term.

**Table 2. Benchmark model: the impact of R&D and ICT on productivity and efficiency**

| | (1) | (2) | (3) | (4) 1973-1994 | (5) 1995-2007 |
|---|---|---|---|---|---|
| *Panel A: Production frontier. Dependent variable: ln(VA)* | | | | | |
| Ln(Labour) | 0.461*** (0.011) | 0.475*** (0.011) | 0.472*** (0.011) | 0.581*** (0.016) | 0.608*** (0.016) |
| Ln(non-ICT) | 0.275*** (0.008) | 0.240*** (0.008) | 0.218*** (0.008) | 0.256*** (0.012) | 0.211*** (0.012) |
| Ln(ICT) | 0.092*** (0.005) | 0.054*** (0.005) | 0.080*** (0.006) | -0.065*** (0.009) | 0.070*** (0.008) |
| Ln(R&D) | 0.201*** (0.002) | 0.195*** (0.002) | 0.153*** (0.002) | 0.173*** (0.003) | 0.141*** (0.003) |
| Time trend (t) | -0.019 (0.016) | -0.020 (0.015) | -0.026* (0.014) | -0.085* (0.047) | 0.020 (0.126) |
| t × ICT (in mill. $) | | 0.052*** (0.008) | -0.002 (0.007) | 2.302*** (0.275) | -0.052*** (0.009) |
| t × R&D (in mill. $) | | 0.126*** (0.004) | 0.124*** (0.003) | 0.133*** (0.010) | 0.096*** (0.003) |
| Constant | 1.260** (0.610) | 1.248** (0.600) | 1.326** (0.558) | 3.644** (1.734) | -0.121 (3.766) |
| *Panel B: Inefficiency equation. Dependent variable: $\ln(\sigma_{u,ijt}^2)$ (logged standard deviation of the inefficiency distribution)* | | | | | |
| Ln(ICT) | | | -0.201*** (0.010) | -0.031** (0.012) | -0.577*** (0.030) |
| Ln(R&D) | | | -0.230*** (0.009) | -0.256*** (0.011) | -0.447*** (0.024) |
| Constant | -2.003*** (0.056) | -1.915*** (0.049) | 0.657*** (0.046) | 0.063 (0.056) | 3.038*** (0.157) |
| *Panel C: Dependent variable: $\ln(\sigma_v^2)$ (logged standard deviation of normally distributed error term)* | | | | | |
| Constant | -1.837*** (0.018) | -1.908*** (0.018) | -2.138*** (0.014) | -2.208*** (0.024) | -2.229*** (0.016) |
| | | | | | |
| Observations | 6332 | 6332 | 6332 | 3412 | 2920 |
| Log-likelihood | -23788.8 | -23171.2 | -21952.0 | -12339.9 | -7057.3 |

[9] Inputs and output are normalized by the mean correction (and taken in logs) so to make the translog frontier's first-order coefficients interpretable as output elasticities.

Notes: standard errors in parentheses. Squares and cross-products of the inputs are not reported. Production function coefficients are expressed as output elasticities. All specifications include industry and country fixed effects and CCE terms. Full tables are available from the authors upon request.

Our analysis starts with the estimation of a baseline frontier model with no efficiency determinants (col. 1). We then extend this specification by including the effect of investment-specific technical change (col. 2) and the impact of R&D and ICT on technical inefficiency (col. 3). In columns (4) and (5) we estimate the full model for the period before and after 1995. This year marks the watershed for the advent of the information revolution and the establishment of knowledge-based economies (as discussed in Section 2). Thus, we check whether the contributions to productivity performance of the different channels have changed over time.

The estimates of prime coefficients of factor inputs in col. (1) are plausible, being consistent with factor income shares reported in Kneller and Stevens (2006) and Badinger and Egger (2016). The coefficient size of the ICT capital (0.092) falls within the range of values found in prior works.[10] Similarly, the magnitude of the coefficient on the within-industry R&D spillovers (0.201) is comparable with Frantzen (2002) and Bloom et al. (2013), among others.

The specification in column (2) shows that the interactions between the time trend and ICT/R&D capital are statistically significant, pointing to a positive effect of these investments on the direction of technical change. The linear trend, taken alone, is not significant, implying that there is no effect associated with exogenous technological change. These results are in accordance with the literature on investment-specific technical change discussed above.

The specification in col. (3) – our benchmark specification - further extends the model to account for the impact of R&D and ICT on technical inefficiency (Panel B of Table 2). The negative coefficient found for both factors indicates that these forms of technological capital reduce inefficiency (namely, the productivity dispersion below the frontier). Following the discussion in Section 1, ICT is likely to decrease inefficiency by improving organisational settings and inter-firm

[10] Reviewing a large number of empirical studies, Kretschmer (2012) concludes that a 1% increase in ICT increases productivity growth by approximately 0.05%.

coordination, while R&D by favouring the adaptation and exploitation of frontier technologies. In a nutshell, this result suggests that investments in technologically advanced assets lead to a better management of production inputs. Furthermore, when including the efficiency channel, the role of R&D and ICT on productivity changes. As we move from col. (2) to col. (3) the ICT elasticity increases (from 0.054% to 0.08%), while the R&D elasticity decreases (from 0.195% to 0.153%). These findings indicate that failing to account for the efficiency impact of technologically advanced assets, as in earlier studies, may yield biased estimates for their productivity effects via input accumulation and spillover channels.

In columns (4) and (5) we estimate our model for two time periods to assess differences in the impact of R&D and ICT over time. Consistent with the existing work (Stiroh, 2002a), we find that ICT accumulation is negatively associated with productivity levels in the first part of our sample period, with an elasticity of -0.065, while the effect of this variable becomes positive from 1995 onwards. Between 1995 and 2007, a 1% increase in ICT increases output by 0.07%. An opposite pattern of results emerges for the ICT-specific technical change, which has a positive productivity effect before 1995 and negative afterwards. This suggests that, in the early stages of diffusion of the new technology, firms could easily gain from outward movements of the production frontier induced by these investments. Once the new technology diffuses, and without further significant movements of the frontier, input accumulation becomes one of the main channels of the productivity growth effect of ICT. On the contrary, the impact of R&D is more robust across the two time periods. Coefficient estimates are slightly lower in the 1995-2007 period compared to earlier years, but they are always positive and statistically significant.

Finally, a crucial insight is that the efficiency impact of ICT and R&D is always significant, positive and increasing over time (especially for ICT). This implies that efficiency gains associated with investments in technologically advanced assets have a broad scope and are not restricted to a particular stage of technology adoption/diffusion or industry life-cycle (Bos et al., 2013).[11]

### *5.2 Industry heterogeneity*

Next, we investigate whether the impact of R&D and ICT varies across industry groups. Since returns of these factors are likely to differ with the technical requirements of production, technological opportunities and appropriability conditions, we distinguish our sample between high-tech and low-tech industries.

Table 3 reports our results. These show that both low-tech and high-tech industries benefit from increasing investments in R&D, albeit the impact is marginally lower in low-tech. Conversely, the effect of ICT capital is positive and significant in high-tech sectors and insignificant in low-tech industries. The latter finding corroborates the idea that the productivity effects of ICT are largely concentrated in those sectors producing goods and services in the field of information technology, whilst they are less diffused elsewhere (Gordon, 2000). We also find evidence of a positive effect of investment-specific technical change, in relation to both innovative assets, but only in high-tech sectors. This indicates that investment-specific technical change contributes to upgrading productivity levels only in industries that most intensively invest in technologically advanced assets or, put it differently, that these technological investments need to overcome a critical threshold to generate significant outward movements of the frontier.

Results for the inefficiency equation reveal that ICT investments always improve efficiency in production, although the effect is much stronger in the high-tech sector. Conversely, R&D capital is negatively related to efficiency levels in high-tech production while it increases efficiency in low-

[11] Papaioannou and Dimelis (2017) find similar results for the impact of ICT on efficiency and relate their increasing effect to the relaxation of product markets regulation in the mid-1990s.

tech industries. This pattern of results, which is consistent with Parelman (1995), would suggest that more innovative industries are less focused on the reduction of technical inefficiency as they enjoy a competitive edge from R&D-induced frontier movements. R&D activities lead to the introduction of new products and processes which, within an industry, shifts the production frontier outward, amplifying the levels of inefficiency below the frontier and making it more difficult for laggards to use the latest technologies, or to cope with the efficiency standards of frontier firms (Castellacci and Zheng, 2010). This is consistent with the firm-level analysis developed by Andrews et al. (2015), who show that the increasingly fiercer competition between global frontier firms, mostly active in high-tech sectors, has widened productivity dispersion below the frontier.

**Table 3. Heterogeneous production frontiers**

| | (1) | (2) |
|---|---|---|
| | High-tech and medium high-tech manufacturing<br>+<br>Knowledge-intensive services | Low-tech and medium low-tech manufacturing<br>+<br>Less knowledge-intensive services |
| *Panel A: Production frontier. Dependent variable: Ln(VA)* | | |
| Ln(Labour) | 0.413***<br>(0.014) | 0.725***<br>(0.016) |
| Ln(non-ICT) | 0.184***<br>(0.01) | 0.148***<br>(0.012) |
| Ln(ICT) | 0.057***<br>(0.007) | 0.006<br>(0.009) |
| Ln(R&D) | 0.165***<br>(0.003) | 0.147***<br>(0.003) |
| Time trend (t) | -0.008<br>(0.019) | -0.019<br>(0.018) |
| t × ICT (in mill. $) | 0.064***<br>(0.008) | -0.028<br>(0.018) |
| t × R&D (in mill. $) | 0.113***<br>(0.003) | -0.047***<br>(0.015) |
| Constant | 1.756**<br>(0.020) | 0.880***<br>(0.049) |
| *Panel B: Inefficiency equation. Dependent variable: $ln(\sigma_{u,ijt}^2)$*<br>*(logged standard deviation of the inefficiency distribution)* | | |
| Ln(ICT) | -0.419***<br>(0.020) | -0.025**<br>(0.012) |
| Ln(R&D) | 0.128***<br>(0.017) | -0.383***<br>(0.012) |
| Constant | -0.778***<br>(0.116) | 0.880***<br>(0.049) |
| *Panel C: Dependent variable: $ln(\sigma_v^2)$*<br>*(logged standard deviation of normally distributed error term)* | | |
| Constant | -2.414***<br>(0.027) | -2.508***<br>(0.025) |
| | | |

| | | |
|---|---|---|
| Observations | 2481 | 3851 |
| Log-likelihood | -6106.1 | -12672.7 |

Notes: Standard errors in parentheses. Squares and cross-products of the inputs are not reported. Production function coefficients are expressed as output elasticities. All specifications include industry and country fixed effects and CCE terms. Full tables are available from the authors upon request.

In low-tech industries, on the other hand, our results show that R&D activities are associated with higher levels of production efficiency as innovations are incremental, more derivative, targeted to softer innovations (organizational, managerial, etc.) and may favour implementation and adaptation of frontier technologies (see Bos et al., 2013 for similar evidence).

Summing up, in high-tech industries R&D efforts are directed towards the creation of breakthrough innovations that increase productivity levels and move the frontier outward, but at the same time raise the inefficiency below the frontier; in low-tech industries R&D is directed towards improving efficiency or implementing frontier technologies (von Tunzelmann and Acha, 2005).

### *5.3 Inter-industry spillovers*

One may question that we are incorrectly estimating the productivity effects of R&D or ICT because these variables capture knowledge transfers or productivity spillovers across industries and countries. Failing to account for these sources of technological knowledge, which are external to the industry, may result into upward biased estimates for both ICT and R&D coefficients. To account for this potential mis-specification problem, we include into the model a measure of inter-industry R&D and ICT spillovers (denoted as *PR&D* and *PICT* respectively) as additional determinants of TFP. We therefore re-write equation (4) as follows:

$$tfp_{ijt} = \theta_1 \cdot \ln R\&D_{ijt} + \theta_2 \cdot \ln PR\&D_{ijt} + \theta_3 \cdot \ln PICT_{ijt} + (\rho_0 \cdot t + \rho_1 \cdot t \cdot ICT_{ijt} + \rho_2 \cdot t \cdot R\&D_{ijt}) - u_{ijt} \quad (4.b)$$

As proxies for the *spillover pool*, we use measures of knowledge generated by investment in ICT and R&D in neighbouring industries (at home or abroad). Hence, we construct, for each industry-country pair, a weighted measure of R&D/ICT, where the weights are the share of intermediate input purchases over total intermediate input expenditure of the purchasing industry. For R&D, our spillover pool variable is defined as:

$$PR\&D_{ijt} = \sum_i \sum_j w_{ij} R\&D_{ijt} \qquad w_{ij} = I_{ij}/(\sum_i \sum_j I_{ij}) \tag{6}$$

where $i$ denotes industries and $j$ denotes countries. $I_{ij}$ identifies inter-industry purchases of intermediate inputs made at home or abroad, derived from the World Input-Output Tables (WIOD) dataset (release 2013).[12] We use the share of intermediates at the benchmark year of 1995 to mitigate problems of reverse causality, which may arise when industries increase their purchases of intermediates from those sectors sourcing larger spillovers. Similarly, for ICT capital, we have:

$$PICT_{ijt} = \sum_i \sum_j w_{ij} ICT_{ijt} \qquad w_{ij} = I_{ij}/(\sum_i \sum_j I_{ij}). \tag{7}$$

As discussed above, our model specification controls for cross-sectional dependence by including CCE terms (Eberhardt et al., 2013). Hence, any effect deriving from the spillover pool variables is additional to the more general effects captured by the cross-sectional averages.

**Table 4. Inter-industry technology spillovers (within and across countries)**

| | (1) | (2) | (3) | (4) | (5) 1973-1994 | (6) 1995-2007 |
|---|---|---|---|---|---|---|
| *Panel A: Production frontier. Dependent variable: ln(VA)* | | | | | | |
| Ln(Labour) | 0.472*** (0.011) | 0.472*** (0.011) | 0.454*** (0.011) | 0.455*** (0.011) | 0.584*** (0.016) | 0.592*** (0.016) |
| Ln(Non-ICT) | 0.218*** (0.008) | 0.225*** (0.008) | 0.240*** (0.008) | 0.242*** (0.008) | 0.254*** (0.012) | 0.216*** (0.012) |
| Ln(ICT) | 0.080*** (0.006) | 0.076*** (0.006) | 0.061*** (0.006) | 0.060*** (0.006) | -0.072*** (0.010) | 0.077*** (0.008) |
| Ln(R&D) | 0.153*** (0.002) | 0.151*** (0.002) | 0.156*** (0.002) | 0.155*** (0.002) | 0.178*** (0.003) | 0.141*** 0.003) |
| Ln(PR&D) | | 0.056*** (0.006) | | 0.0240*** (0.006) | 0.048*** (0.008) | 0.011 (0.009) |
| Ln(PICT) | | | 0.177*** (0.008) | 0.169*** (0.008) | 0.144*** (0.013) | 0.089*** (0.014) |
| Time trend (t) | -0.026* (0.014) | -0.015 (0.019) | -0.032** (0.014) | -0.025 (0.019) | -0.059 (0.063) | 0.000 (0.000) |
| t × ICT (in mill. $) | -0.002 (0.007) | 0.003 (0.007) | -0.011 (0.007) | -0.0081 (0.007) | 2.525*** (0.277) | -0.052*** (0.009) |
| t × R&D (in mill. $) | 0.124*** (0.003) | 0.131*** (0.003) | 0.120*** (0.003) | 0.123*** (0.003) | 0.141*** (0.010) | 0.097*** (0.004) |
| Constant | 1.326** (0.558) | 0.871 (0.697) | 0.963 (0.600) | 0.747 (0.702) | 2,035 (2.651) | 0.449 (4.645) |

[12] We set within-industry intermediate transactions to zero so that the matrix of weights has null cells along the principal diagonal.

| | | | | | | |
|---|---|---|---|---|---|---|
| *Panel B: Inefficiency equation. Dependent variable: $ln(\sigma_{u,ijt}^2)$* <br> *(logged standard deviation of the inefficiency distribution)* | | | | | | |
| Ln(ICT) | -0.201*** | -0.205*** | -0.197*** | -0.199*** | -0.037*** | -0.565*** |
| | (0.010) | (0.010) | (0.010) | (0.010) | (0.013) | (0.030) |
| Ln(R&D) | -0.230*** | -0.227*** | -0.240*** | -0.238*** | -0.249*** | -0.451*** |
| | (0.009) | (0.009) | (0.009) | (0.009) | (0.010) | (0.025) |
| Constant | 0.657*** | 0.696*** | 0.671*** | 0.684*** | 0.120** | 2.982*** |
| | (0.046) | (0.045) | (0.045) | (0.045) | (0.057) | (0.158) |
| *Panel C: Dependent variable: $ln(\sigma_v^2)$* <br> *(logged standard deviation of normally distributed error term)* | | | | | | |
| Constant | -2.138*** | -2.160*** | -2.150*** | -2.158*** | -2.271*** | -2.230*** |
| | (0.014) | (0.015) | (0.014) | (0.014) | (0.025) | (0.016) |
| Observations | 6332 | 6332 | 6332 | 6332 | 3412 | 2920 |
| Log-likelihood | -21952.0 | -21903.2 | -21684.7 | -21676.0 | -1.2e+04 | -7.0e+03 |

Notes: Standard errors in parentheses. Squares and cross-products of the inputs are not reported. Production function coefficients are expressed as output elasticities. All specifications include industry and country fixed effects and CCE terms. Full tables are available from the authors upon request.

Table 4 reports our results for the extended specification. The first column reproduces the coefficient estimates for the benchmark specification (Table 2, col. 3) for comparison purposes, while columns (2) – (6) include our proxies for inter-industry spillovers. We consider these variables separately in columns (2) and (3), whilst in column (4) we include them in the same specification. These measures of inter-industry spillovers are positively and significantly related to industry value added. Estimates suggest that a 1% increase in the value of our spillover pools increases productivity by 0.06% in the case of R&D, and 0.177% for ICT. The estimated impact is lower when we include both proxies in the same specification (0.024% for R&D and 0.169% for ICT), which is probably due to the correlation induced by the same structure of weights used in their construction. Nonetheless, both spillover variables remain highly significant.[13] Our findings therefore diverge from Acharya (2016) who stresses that, at the industry-by-country level, it is difficult to discern inter-industry ICT spillovers from those induced by the R&D investments of commercial partner industries (which usually prevail). Focusing on column (4), our results show that the inter-industry spillover effect of R&D is noticeably smaller than the excess returns associated with the (within-) industry R&D engagement (0.024 vs. 0.155, col. 3). We observe a similar pattern in columns (5) and (6), where we split the sample into pre- and post-1995. In the later period inter-industry R&D spillovers are no longer statistically significant. This may be due to the increasing difficulty of R&D to turn into

[13] Similar findings emerge even when we use weights scaled on the total sales of the selling industry, or use weights for a benchmark country (the US). We omit these results for sake of brevity.

innovation output and the reduced potential for technology transfers (Segerstrom, 1998; Venturini, 2012; Bloom et al., 2017). Conversely, the inter-industry spillover effect of ICT plays an important role in the overall period (col. 4), although the effect is lower after 1995.[14]

Our results on inter-industry spillover effects from ICT and R&D are consistent both in size and significance with Marsh et al. (2017). Using US firm-level data for the 1990s, these authors show that productivity spillovers of the inter-industry ICT pool are positive and robust across specifications, whilst R&D spillovers channelled by inter-industry intermediate input transactions are not statistically significant.

### *5.4* **C***omplementarities between ICT and R&D*

Current discussions on the relationship between ICT, R&D and productivity suggest the presence of complementarities between the two innovative assets (Polder et al., 2017; Corrado et al., 2017). In this section we contribute to these new developments by investigating whether ICT and R&D act as complements in reducing inefficiencies in production. To address this question, we include into our specification an interaction term in the efficiency component of the model. Table 5 presents the results relative to the inefficiency equation (*Panel B*), including estimates of the benchmark model in the first column (see Appendix Table A.3 for the full table). Column (2) refers to the specification without inter-industry spillovers, while these are included in column (3). These results show that the interaction between ICT and R&D is negative and statistically significant, indicating the presence of complementarities between the two assets in reducing technical inefficiency. The estimated individual effects of ICT and R&D are lower (cols. 2 and 3 vs. column 1) which suggests that omitting the interaction term inflates the direct effect of ICT and R&D.

These findings suggest that ICT may complement R&D in the re-organization of production during the innovation process, consistent with Polder et al. (2017). ICT may also facilitate the

[14] See Section A.1 of the Appendix (Table A.4) for an extended assessment of the sensitivity of the results to the modelling of cross-sectional dependence.

diffusion of best practices, leading to better resource management and coordination (Corrado et al., 2017). Our results also support the evidence discussed in Chen et al. (2016), where industries with a higher ICT usage intensity enjoy larger returns to R&D and organizational investments. However, the identification of the exact mechanisms through which the complementarity between technological investments operates requires more information about the nature (basic, applied, or development) and the composition (personnel, equipment, structures, etc.) of R&D, as well as about the type (computers, software, EPR, platforms, etc.) and the field of application (commercial, administrative, etc.) of ICT. This is an important area for further research.

**Table 5. Complementarity effects on technical efficiency (full specification)**

| *Panel B: Inefficiency equation. Dependent variable: ln($\sigma_{u,ijt}^2$) (logged standard deviation of the inefficiency distribution)* | | | |
|---|---|---|---|
| | (1) | (2) | (3) |
| Ln(ICT) | -0.201***<br>(0.010) | -0.140***<br>(0.011) | -0.147***<br>(0.011) |
| Ln(R&D) | -0.230***<br>(0.009) | -0.144***<br>(0.011) | -0.157***<br>(0.011) |
| Ln(ICT) × Ln(R&D) | | -0.021***<br>(0.002) | -0.019***<br>(0.002) |
| Constant | 0.657***<br>(0.046) | 0.469***<br>(0.046) | 0.517***<br>(0.045) |
| | | | |
| Spillovers variables in the frontier | No | No | Yes |
| Observations | 6332 | 6332 | 6332 |

Notes: Standard errors in parentheses. All specifications include industry and country fixed effects and CCE terms. Translog production function coefficients and the standard deviation of the normally distributed error term omitted to save space. The complete set of coefficients is shown in Appendix Table A.3.

## 6 Assessing the relevance of ICT and R&D

### *6.1 Contribution of ICT and R&D to output and TFP growth*

We have so far identified different ways in which ICT and R&D affect output production, i.e. via input accumulation, spillover channel, technical change and technical efficiency. We now turn to evaluating the overall contribution of the different channels to output and TFP growth over our sample period. More specifically, we now quantify the proportion of the output growth that, according to our model, is due to changes in input accumulation and TFP growth, and more importantly how much TFP growth is due to R&D and ICT, via the different channels (eq. 4.b). The derivation of the respective components is shown in Sections A.2 and A.3 of the Appendix.

Table 6 reports our results. Our model predicts a positive output growth throughout the period, driven to a large extent by TFP growth and, secondarily, by capital accumulation (ICT and non-ICT capital). The contribution of labour accumulation is negative (-0.27%).

**Table 6. Sources of output and TFP growth (1973-2007)**

| | | |
|---|---|---|
| | **Output growth (predicted)** | **7.34%** |
| **Components of output growth** | **Input accumulation (total)** | **1.15%** |
| | Labor accumulation | -0.27% |
| | Non-ICT capital accumulation | 0.61% |
| | ICT capital accumulation | 0.81% |
| | **TFP growth** | **6.23%** |
| **Contributions to TFP growth** | **Total R&D capital contribution** | **56.6%** |
| | Within-industry R&D spillovers | 22.4% |
| | R&D investment-specific TC | 30.9% |
| | Inter-industry R&D spillover | 2.4% |
| | R&D contribution to TFP growth via efficiency | 0.9% |
| | **Total ICT capital contribution** | **36.8%** |
| | ICT investment-specific TC | -0.7% |
| | Inter-industry ICT spillovers | 36.8% |
| | ICT contribution to TFP growth via efficiency | 0.7% |

The decomposition shows that R&D and ICT have accounted for almost 95% of TFP growth. R&D has played a key role, particularly via within-industry spillovers (extra-returns) and investment-specific technical change. The ICT capital contribution is lower than the R&D contribution (36.8% versus 56.6%), but it is still sizeable. The main contribution comes from inter-industry spillovers, a result which is consistent with the larger share of knowledge made possible by the diffusion of ICT applications (Marsh et al., 2017). On the other hand, spillovers from R&D predominantly transmit *within* rather than *across* industries, probably because of the more specific knowledge content and greater similarities in the technology base between firms operating in the same sector.

Finally, Table 6 shows that R&D and ICT contribute to TFP growth via the efficiency channel by a 0.9% and 0.7%, respectively, a smaller effect compared to the other channels. Consistently to what found in earlier papers (Henry et al., 2009; Bos et al., 2010), efficiency change overall explains approximately 1% of TFP growth (see the full decomposition in Table A.5). This is hardly surprising given that we are looking at a group of industrialised countries which are expected to be close to the technological frontier. As shown in Table 3, deviation from the frontier are more likely to be related to the turbulence of research activity rather than an inefficient use of factor inputs.

### *6.2 Policy implications*

Our results have important implications for policy measures aimed at increasing productivity growth. Throughout our study we have analysed the impact of R&D next to ICT, emphasising the notion that modern production systems need to focus on the contribution of both research and digital technologies. This is at the centre of the Fourth Industrial Revolution and the Internet of Things (WEF, 2017), based on hyper-connectivity, the use of machine learning algorithms, big data and robotization. This new framework involves a greater integration of investments in R&D and information technology in driving smart production (EPO, 2017; Schwab, 2016). To date there is only some initial evidence that highly automated production modes and intelligent technologies have positive effects on productivity (Graetz and Michaels, 2017; Venturini, 2018) and our analysis provides an early contribution to this new strand of the literature.

Our results suggest that policy initiatives aimed at raising the joint engagement in R&D and advanced information systems will yield large effects in the medium and long run, will exploit different transmission channels and produce heterogeneous impacts across industries. Examples of these policies in OECD countries include Alliance Industrie du Future (France), Plattform Industrie 4.0 (Germany) and Piano Industria 4.0 (Italy). These have introduced cumulative incentives to technological investments such as R&D tax credits, patent box and enhanced deductions to investments in tangible and intangible assets, i.e., special tax treatments to expenditure in scientific software and electronic equipment employed in the realisation of R&D projects.

Finally, our analysis also highlights the importance of inter-industry ICT spillovers in promoting productivity growth. With the advent of the Fourth Industrial Revolution, these effects may be larger than those estimated in the current study, suggesting that public incentives towards the adoption of intelligent technologies might spur productivity indirectly via inter-industry ICT spillovers.

## 7. Conclusions

This paper has provided a comprehensive assessment of the productivity growth effects of R&D and ICT, using long-term data for a large cross-country, cross-industry sample. Looking at the full spectrum of channels through which these investments can translate into better productivity performance - namely input accumulation, investment-specific technical change, efficiency and spillover - we have identified what proportion of industrial productivity growth can be ascribed to ICT and R&D.

We have shown that R&D operates through all main routes: i) a direct impact on TFP; ii) by promoting investment-specific technical change; iii) by increasing production efficiency; and iv) by generating spillovers. On the other hand, the productivity effect of ICT works through a lower number of channels whose relevance has changed over time, i.e. investment-specific technical change and efficiency route before 1995, input accumulation after 1995, whilst inter-industry spillover effects have been significant throughout the 1973-2007 period. We have also found some evidence of complementarity between R&D and ICT in reducing inefficiencies in production. When accounting for industry heterogeneity, we have shown that ICT has wide positive effects on efficiency across sectors. By contrast, R&D increases efficiency in low-tech industries but not in high-tech industries, in which it probably raises efficiency dispersion because of the introduction of radical, breakthrough innovations, and the simultaneous process of creative destruction.

Our results provide valuable insights into the role of technological investments on TFP growth. First, both ICT and R&D are found to explain almost all of the productivity growth in developed countries since the early 1970s. The magnitude of the effect appears much larger than found in works using similar data (Mc Morrow et al., 2010). Second, contrary to previous estimates (Stiroh, 2002b; Inklaar et al., 2008), investments in ICT capital produce sizable spillover effects on TFP and hence their contribution to explaining the EU-US productivity divide may be larger than estimated in earlier works (Timmer and Van Ark, 2005). This also calls for further analysis into how industry structure within countries, and differences in ICT intensity across companies, contribute to productivity growth. These questions have been investigated in relation to R&D (Moncada-Paternò-Castello et al., 2010), while the evidence for ICT is rather limited (Chun et al., 2015).

Overall, our work has contributed to a better understanding of the complex mechanisms (channels) through which technological investments affect productivity growth. We have employed a methodological framework that can be used to analyse the drivers of productivity growth in different countries and time periods and that may help understand the productivity slowdown in advanced economies, following the Great Recession of 2008-2009. We leave these developments open to future research.

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## Appendix

**Table A.1. Summary statistics**

| | Observations | Mean | Standard deviation | Min. | Max. |
|---|---|---|---|---|---|
| **1973-1994** | | | | | |
| Value added | 3,412 | 19,827.3 | 28,012.4 | 22.5 | 201,376.0 |
| Total hours worked | 3,412 | 987.0 | 1,278.7 | 4.6 | 7,856.0 |
| Non-ICT capital stock | 3,412 | 8,069.7 | 11,928.2 | 21.9 | 74,461.0 |
| ICT capital stock | 3,412 | 309.3 | 742.9 | 0.0 | 8,249.9 |
| R&D stock | 3,412 | 4,173.4 | 16,173.8 | 0.0 | 197,137.1 |
| **1995-2007** | | | | | |
| Value added | 2,920 | 38,417.7 | 104,763.2 | 61.0 | 1,469,737.9 |
| Total hours worked | 2,920 | 1,171.7 | 3,121.5 | 2.6 | 43,675.0 |
| Non-ICT capital stock | 2,920 | 13,432.9 | 28,994.7 | 57.8 | 300,853.7 |
| ICT capital stock | 2,920 | 3,465.8 | 13,652.1 | 0.8 | 220,458.8 |
| R&D stock | 2,920 | 7,750.7 | 28,611.9 | 0.9 | 355,314.7 |
| **1973-2007** | | | | | |
| Value added | 6,332 | 28,400.3 | 74,625.7 | 22.5 | 1,469,737.9 |
| Total hours worked | 6,332 | 1,072.1 | 2,319.9 | 2.6 | 43,675.0 |
| Non-ICT capital stock | 6,332 | 10,542.9 | 21,712.2 | 21.9 | 300,853.7 |
| ICT capital stock | 6,332 | 1,765.0 | 9,418.4 | 0.0 | 220,458.8 |
| R&D stock | 6,332 | 5,823.1 | 22,837.8 | 0.0 | 355,314.7 |

Note: monetary variables are expressed in millions of USD PPP 1997; hours worked are expressed in thousands of hours.

**Table A.2 Specification tests**

| **Null hypothesis** | **Conditions** | **Chi$^2$ statistics** | **Critical values (5%)** |
|---|---|---|---|
| Cobb-Douglas | $\beta_{np}$=0, for n,p=L, K, ICT | 1727.00 | 21.02 |
| Constant Returns to Scale | $\Sigma\beta_n$=1, for n=L, K, ICT; $\Sigma\beta_{np}$=0, for n,p=L, K, ICT; | 896.76 | 9.48 |
| No inefficiency | $\lambda = 0$ | 280.00 | 2.71 |
| No common correlated effects | No significance of the coefficients of the cross-sectional averages of dependent and independent variables | 96.28 | 19.67 |
| No technical change components | $\rho_1$=0 & $\rho_2$=0 & $\rho_3$=0 | 1650.00 | 7.81 |

Notes: these tests refer to the specification in Col. 3, Table 2. The only exception is raw 3 which refers to Col. 2, Table 2.

## Appendix Table A.3. Complementarity between ICT and R&D

| | (1) | (2) | (3) |
|---|---|---|---|
| *Panel A: Production frontier. Dependent variable: ln(VA)* | | | |
| Ln(Labour) | 0.472***<br>(0.011) | 0.477***<br>(0.011) | 0.459***<br>(0.010) |
| Ln(non-ICT) | 0.218***<br>(0.008) | 0.217***<br>(0.008) | 0.241***<br>(0.008) |
| Ln(ICT) | 0.080***<br>(0.006) | 0.067***<br>(0.006) | 0.048***<br>(0.006) |
| Ln(R&D) | 0.153***<br>(0.002) | 0.150***<br>(0.002) | 0.152***<br>(0.002) |
| Ln(PR&D) | | | 0.028***<br>(0.006) |
| Ln(PICT) | | | 0.162***<br>(0.008) |
| Time trend (t) | -0.026*<br>(0.014) | -0.026*<br>(0.014) | -0.025<br>(0.019) |
| t × ICT (in mill. $) | -0.002<br>(0.007) | 0.010<br>(0.007) | 0.003<br>(0.007) |
| t × R&D (in mill. $) | 0.124***<br>(0.003) | 0.126***<br>(0.003) | 0.126***<br>(0.003) |
| Constant | 1.326**<br>(0.558) | 1.305**<br>(0.555) | 0.737<br>(0.699) |
| *Panel B: Inefficiency equation. Dependent variable: ln($\sigma_{u,ijt}^2$),*<br>*(logged standard deviation of the inefficiency distribution)* | | | |
| Ln(ICT) | -0.201***<br>(0.010) | -0.140***<br>(0.011) | -0.147***<br>(0.011) |
| Ln(R&D) | -0.230***<br>(0.009) | -0.144***<br>(0.011) | -0.157***<br>(0.011) |
| Ln(ICT) x Ln(R&D) | | -0.021***<br>(0.002) | -0.019***<br>(0.002) |
| Constant | 0.657***<br>(0.046) | 0.469***<br>(0.046) | 0.517***<br>(0.045) |
| *Panel C: Dependent variable: ln($\sigma_v^2$ )*<br>*(logged standard deviation of normally distributed error term)* | | | |
| Constant | -2.138***<br>(0.014) | -2.138***<br>(0.014) | -2.159***<br>(0.014) |
| Observations | 6332 | 6332 | 6332 |
| Log-likelihood | -2.2e+04 | -2.2e+04 | -2.2e+04 |

Notes: standard errors in parentheses. Squares and cross-products of the inputs are not reported to save space. Production function coefficients are expressed as output elasticities. All specifications include industry and country fixed effects and CCE terms.

### *A.1 Robustness checks on cross-sectional dependence (CCE) terms*

As a further robustness check, we have assessed the sensitivity of our results to different assumptions regarding the control for cross-sectional dependence (Appendix Table A.4). In the manuscript, we have used pooled CCE terms within the frontier, i.e. we have imposed common coefficients on the cross-sectional averages of the dependent and independent variables. Here, we assess the robustness of our results to the inclusion of CCE terms in the inefficiency equation (Table A.4, col. 2) and in both the frontier and the efficiency term (Table A.4, col. 3). In both cases, our findings are not significantly altered and the main difference is a moderately lower impact of ICT and R&D on efficiency (Table A.4, col. 3). We also take another step forward, allowing for heterogeneity in the parameters associated with CCE terms. We first assume that the coefficients on the cross-sectional terms vary by countries but are common across industries (Table A.4, col. 4). In the last column of Table A.4, the parameters of the CCE are allowed to vary across industries. These changes in the treatment of the cross-sectional terms control for the possibility that un-observed factors affect countries or industries asymmetrically. In our model, this robustness check could be particularly useful to remove the noise associated with the measurement of ICT and, to some extent, R&D. Overall, the magnitude of all estimated parameters is largely similar to the benchmark model (col. 3, Table 2), with the exception of ICT whose impact on efficiency is larger when using country-specific coefficients for the CCE terms.

## Table A.4 Robustness checks: Alternative modelling for cross-sectional dependence

| | Pooled CCE | | | Heterogeneous CCE | |
|---|---|---|---|---|---|
| | (1) | (2) | (3) | (4) | (5) |
| *Panel A: Production frontier. Dependent variable: ln(VA)* | | | | | |
| Ln(Labour) | 0.472***<br>(0.011) | 0.480***<br>(0.011) | 0.485***<br>(0.012) | 0.496***<br>(0.011) | 0.616***<br>(0.011) |
| Ln(non-ICT) | 0.218***<br>(0.008) | 0.211***<br>(0.008) | 0.217***<br>(0.008) | 0.243***<br>(0.008) | 0.163***<br>(0.008) |
| Ln(ICT) | 0.080***<br>(0.006) | 0.080***<br>(0.006) | 0.0790***<br>(0.006) | 0.044***<br>(0.006) | 0.0632***<br>(0.006) |
| Ln(R&D) | 0.153***<br>(0.002) | 0.156***<br>(0.002) | 0.159***<br>(0.003) | 0.173***<br>(0.002) | 0.153***<br>(0.002) |
| Time trend (t) | -26.21*<br>(14.34) | -1.533**<br>(0.670) | -32.17**<br>(14.25) | -0.022<br>(0.015) | -26.76**<br>(13.62) |
| t × ICT (in mill. $) | -0.002<br>(0.007) | 0.002<br>(0.007) | -0.006<br>(0.007) | -0.021***<br>(0.008) | -0.020***<br>(0.007) |
| t × R&D (in mill. $) | 0.124***<br>(0.003) | 0.122***<br>(0.003) | 0.121***<br>(0.003) | 0.114***<br>(0.003) | 0.093***<br>(0.003) |
| Constant | 1.326**<br>(0.558) | 0.790***<br>(0.029) | 0.813<br>(0.665) | 0.917<br>(1.279) | 1.056<br>(1.680) |
| *Panel B: Inefficiency equation. Dependent variable: ln($\sigma_{u,ijt}^2$)*<br>*(logged standard deviation of the inefficiency distribution )* | | | | | |
| Ln(ICT) | -0.201***<br>(0.010) | -0.187***<br>(0.010) | -0.175***<br>(0.010) | -0.184***<br>(0.010) | -0.205***<br>(0.009) |
| Ln(R&D) | -0.230***<br>(0.009) | -0.211***<br>(0.009) | -0.203***<br>(0.009) | -0.258***<br>(0.010) | -0.255***<br>(0.009) |
| Constant | 0.657***<br>(0.046) | -0.368<br>(1.916) | -4.705*<br>(2.813) | 0.548***<br>(0.048) | 0.856***<br>(0.045) |
| *Panel C: Dependent variable: ln($\sigma_v^2$)*<br>*(logged standard deviation of normally distributed error term)* | | | | | |
| Constant | -2.138***<br>(0.014) | -2.154***<br>(0.014) | -2.166***<br>(0.015) | -2.137***<br>(0.014)) | -2.358***<br>(0.016) |
| | | | | | |
| Industry dummies | Yes | Yes | Yes | Yes | Yes |
| Country dummies | Yes | Yes | Yes | Yes | Yes |
| Common Correlated Effects | Frontier | Efficiency | Frontier+<br>Efficiency | Frontier | Frontier |
| Common Correlated Effects (parameters) | Common | Common | Common | Country-<br>specific | Industry-<br>specific |
| | | | | | |
| Observations | 6332 | 6332 | 6332 | 6332 | 6332 |
| Log-likelihood | -21952.0 | -21939.4 | -21863.3 | -20958.5 | -19651.0 |

Notes: standard errors in parentheses. Squares and cross-products of the inputs are not reported to save space. Production function coefficients are expressed as output elasticities. All specifications include industry and country fixed effects and CCE terms.

### A.2 Derivation of the contribution of the different channels to output and productivity growth

The computation of the contribution of the different channels to output and TFP growth has been carried out as follows:

i) input accumulation (*IA*), IA=$\sum_n(\gamma_{n,ijt} \cdot \dot{x}_n)$, where $\dot{x}$ is the annual rate of input growth[15];

ii) technical change ($TC$): $TC_{ijt} = \frac{\partial y_{ijt}}{\partial t} = \rho_0 + \rho_1 \cdot ICT_{ijt} + \rho_2 \cdot R\&D_{ijt}$;

iii) within-industry R&D spillover $\theta \cdot R\dot{\&}D_{ijt}$;

iv) efficiency change ($EC$), $EC = -\frac{\partial \mathrm{u}_{ijt}}{\partial \mathrm{t}} \cong -(u_{ijt} - u_{ijt-1})$

v) scale changes ($SC$), $SC = \left(RTS_{n,ijt} - 1\right) \cdot \sum_n \left[\left(\frac{\gamma_{n,ijt}}{RTS_{n,ijt}}\right) \cdot \dot{x}_n\right]$

Thus, for our benchmark model we can re-write the output growth equation as follows:

$$\dot{y}_{ijt} = \underbrace{\textstyle\sum_n(\gamma_{n,ijt} \cdot \dot{x}_n)}_{Input\ accumulation} + \underbrace{\theta \cdot R\dot{\&}D_{ijt} + TC + EC + SC}_{T\dot{F}P} \tag{8}$$

When including inter-industry spillover effect we add two additional terms to eq. (8):

$$\dot{y}_{ijt} = \underbrace{\textstyle\sum_n(\gamma_{n,ijt} \cdot \dot{x}_n)}_{Input\ accumulation} + \underbrace{\theta \cdot R\dot{\&}D_{ijt} + TC + EC + SC}_{T\dot{F}P} + \underbrace{(\theta_2 \cdot PR\dot{\&}D_{\iota jt})}_{inter-industry\ R\&D\ spillover} + \underbrace{(\theta_3 \cdot PIC\dot{T}_{\iota jt})}_{inter-industry\ ICT\ spillover} \tag{9}$$

[15] Output elasticity of each input *n* is $\gamma_{n,ijt} = \frac{\partial y_{ijt}}{\partial x_{nijt}} = \beta_n + (\beta_{nn} \cdot x_{n,ijt}) + \sum_{p \neq n} \beta_{np} \cdot x_{p,ijt}$ and returns to scale ($RTS_{n,ijt}$) are $\sum_n \gamma_{n,ijt}$ . In a translog production function both output elasticities and returns to scale are specific to each observation (industry/country/year). In our case, also the technical change (investment-specific) component is specific to each observation.

### A.3 Derivation of the marginal effects of technological investments on inefficiency

For the given parameterization of the normal-half-normal SFM (Kumbhakar et al., 2017), the marginal effect of ICT on $E[u_{ijt}|\ln ICT_{ijt}, \ln R\&D_{ijt}]$ is:

$$\frac{\partial E[u_{ijt}|\ln ICT_{ijt}, \ln R\&D_{ijt}]}{\partial \ln ICT_{ijt}} = \delta_1 \cdot \sqrt{\frac{2}{\pi}} \cdot \sigma_{u,ijt}.$$

The marginal effect of R&D is:

$$\frac{\partial E[u_{ijt}|\ln ICT_{ijt}, \ln R\&D_{ijt}]}{\partial \ln R\&D_{ijt}} = \delta_2 \cdot \sqrt{\frac{2}{\pi}} \cdot \sigma_{u,ijt}.$$

**Table A.5. Sources of output and TFP growth: Full decomposition**

| | | % points |
|---|---|---|
| **Output growth (predicted)** | **a (=b+c)** | **7.34%** |
| **Input accumulation** | **b (=b1+b2+b3)** | **1.15%** |
| Labour accumulation | b1 | -0.27% |
| Non-ICT capital accumulation | b2 | 0.61% |
| ICT capital accumulation | b3 | 0.81% |
| **TFP growth** | **c (=c1+..+c7)** | **6.23%** |
| Within-industry R&D spillovers | c1 | 1.40% |
| ICT investment-specific technical change (TC) | c2 | -0.05% |
| R&D investment-specific technical change (TC) | c3 | 1.92% |
| Scale change | c4 | -0.37% |
| Inter-industry R&D spillovers | c5 | 0.15% |
| Inter-industry ICT spillovers | c6 | 2.29% |
| Efficiency change | c7 | 0.88% |
| *R&D contribution to TFP growth via efficiency* | *d1=marg. effect*c7* | *0.05%* |
| *ICT contribution to TFP growth via efficiency* | *d2=marg. effect*c7* | *0.04%* |

| | | |
|---|---|---|
| **TFP growth** | | **100.0%** |
| **Total R&D capital contribution** | | **56.6%** |
| Within-industry R&D spillovers | c1/c | 22.4% |
| R&D investment-specific TC | c3/c | 30.9% |
| Inter-industry R&D spillovers | c5/c | 2.4% |
| R&D contribution to TFP growth via efficiency | d1/c | 0.9% |
| **Total ICT capital contribution** | | **36.8%** |
| ICT investment-specific TC | c2/c | -0.7% |
| Inter-industry ICT spillovers | c6/c | 36.8% |
| ICT contribution to TFP growth via efficiency | d2/c | 0.7% |