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

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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 TFP growth documenting that R&D and ICT accounted for almost 95% of TFP growth in the OECD area.

Keywords**:** Research & Development; Information and Communication Technology; Productivity; Stochastic frontier models

JEL classification: O14, O32, O47

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1. Introduction

What do we know about the drivers of productivity? Which are the channels through which innovative investments translate into better productivity performance? The economic growth literature is still debating which factors produce long-lasting effects on productivity and explain cross-country productivity differentials (Madsen 2008, Cette et al. 2016). Such studies find a renewed motivation in the latest theories of endogenous growth, which claim that the intensity of innovation activities persistently raise the rate of productivity growth, and hence living standards, in the long run (Aghion and Howitt 1998, Dinopoulos and Thompson 1998).

Empirically, innovative activities, typically proxied by investment in 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). Since the mid-1990s, research has also focused on Information and Communication Technologies (ICT) and various contributions confirm their importance in driving productivity growth (O'Mahony and Vecchi 2009, Venturini 2009). A feature of this literature is that the role of R&D and ICT has often been analysed separately, ignoring possible correlations between the two assets in the production process (Polder et al. 2017). However, if R&D and ICT are both important in promoting productivity performance, and if they are correlated, omitting one of them from the analysis could seriously affect the identification of the true drivers of productivity. Evidence on the joint role of the two assets has been provided by Hall et al. (2013) at the firm level and Venturini (2015) at the country level, both concluding that these investments have independent effects on Total Factor Productivity (TFP). Conversely, Corrado et al. (2017) document the presence of complementarities between ICT and intangible capital, which include not only R&D but other innovative activities such as new architectural and engineering design and new product development. However, apart from these few exceptions, the literature is silent about the joint productivity impact of R&D and ICT and the channels through which they affect productivity growth. 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 R&D and ICT investments promote the diffusion of technological knowledge across firms, both within the country and internationally (Coe and Helpman 1995). The empirical evidence has given strong support to the role of R&D as a factor of production and to its ability to generate spillovers, although the magnitude of private and social returns to R&D is still subject to debate (Eberhardt et al. 2013, Ugur et al. 2016). As for ICT, the input accumulation channel was initially believed to be of limited importance (Gordon 2000), but a second wave of studies has provided evidence 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, and similar conclusions have been reached by Haskel and Wallis (2013) for the UK and Inklaar et al. (2008) for the EU. 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, Moshiri and Simpson 2011, Moshiri, 2016, Marsh et al. 2017).

A typical feature of this literature is to rely on the implicit assumption that factor inputs are fully utilized and that there is no slack in production activities, i.e. all economic units – firms, industries, countries - 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 factor inputs to produce a given level of output. Studies on the impact of R&D and ICT on productivity, via promoting efficiency, have not presented so far consistent evidence. For example, Kneller and Stevens (2006) show that technical efficiency is positively

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

influenced by human capital, whilst R&D investments appear to be a determinant of technical change (i.e, they shift the production frontier outward) but they do not affect technical efficiency (i.e. they do not reduce the gap with the frontier). Bos et al. (2013) extend this line of analysis, documenting that R&D contributes to higher efficiency levels in mature industries, while it decreases efficiency in young industries. As for ICT, the General-Purpose Technology (GPT) literature has put forward the link between the new technology and organizational changes (Jovanovic and Rousseau 2005, Bresnahan and Trajtenberg, 1995, Lipsey et al. 2005). 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). It is reasonable to assume that these developments contribute to a more efficient use of factor inputs within the production process. Some evidence in this respect is provided by Becchetti et al. (2003) and Castiglione (2012) for Italian firms, and Papaioannou and Dimelis (2017) for US and European industries. Overall, these studies support the role of ICT in reducing inefficiency; however, the industry-level evidence suggests that the effect is weaker in high-tech sectors.

Potentially, there is also a *fourth* channel of impact of 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), it is recognized that technical change may not be neutral but specific to firms' investment in new vintages of capital goods that embody the latest technologies (so-called investment-specific technical change). Greenwood et al. (1997) provide empirical support to this theoretical prediction, showing that the largest proportion of output growth in the US is due to technical change, enabled by investments in machinery and equipment. Samaniego (2007) extends this analysis to the inclusion of investments in knowledge assets, finding that R&D-driven technical change, rather than TFP, explains output growth in developed countries. Venturini (2007) and Martínez et al. (2010) reveal the importance of ICT-driven technical change in promoting productivity growth in the US. However, the relative importance of investment-specific technical change, next to other possible ways in which capital assets can affect growth, is still unknown.

This paper investigates the joint 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 output and TFP growth. Throughout the analysis we control for cross-sectional dependence (CSD), 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 play an important role in increasing productivity levels through the different channels, with significant differences over time and across different types of industries. R&D drives productivity through all the proposed routes, whilst ICT operates via investment-specific technical change and efficiency pre-1995 and input accumulation post-1995. Our analysis provides evidence of important inter-industry spillovers, associated with both R&D and ICT, and supports the presence of complementarity between R&D and ICT in reducing inefficiencies in production. Finally, we show that all transmission channels considered in the study contribute to TFP growth, with inter-industry ICT spillovers and R&D-specific technical change playing the most important roles. Together, R&D and ICT make up 95% of TFP growth in OECD countries, a result that confirms the importance of accounting for the joint role of the two assets.

This study contributes to the growing literature that investigates the interplay between tangible and intangible assets (R&D, brands, economic competencies, etc.). Papers have shown that these assets explain a significant proportion of the growth in total factor productivity in recent years (Corrado et al. 2017, Niebel et al. 2017), but their impact via technical change and technical efficiency is largely unknown. Our analysis adds to the interpretation of how investments in intangible assets, which include both R&D and computerized software among others, translate into greater productivity outcomes. In addition, recognising the role of efficiency alongside technical change and spillovers is important to obtain a correct evaluation of the different components of TFP. If new technologies are not going to be as 'revolutionary' as the innovations in the past (Gordon 2016), then one of the possible sources of productivity gains in mature economies is greater efficiency, i.e. a greater ability to exploit existing resources, given that long-run economic growth is bound by diminishing returns on conventional inputs (Van Ark et al. 2011). 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). In this respect, the present paper offers a novel contribution to the productivity debate (Jorgenson et al. 2016).

The structure of the paper is the following. The next section presents our analytical framework, showing the modelling of the different channels within a SFM framework. Section 3 presents the data used in the empirical analysis and Sections 4 and 5 presents our results, as well as discussing robustness tests. Section 6 quantifies the contribution of R&D and ICT to productivity growth for the period covered by our analysis. Finally, Section 7 concludes the paper.

2. Analytical framework

2.1 A stochastic frontier production model

Our analysis is based on a frontier production function, which identifies the maximum output achievable, given the current production technology and available inputs[2]. In a panel data setting, in which i's denote industries, j's countries, and t's time observations, the maximum output (Y^*_{ijt}) is the boundary level of a common production set and the frontier can be expressed as (see Bos et al., 2010, pp. 62-63; among others):

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

[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.

where X_{ijt} is a set of inputs, β is a vector of technology parameters and v_{ijt} is an i.i.d. error term. The disturbance term is distributed as a $N(0, \sigma_v^2)$ and captures departures from the predicted-by-the-model output that are due to unobserved random shocks and measurement errors. Industries that lie below the frontier are characterised by production inefficiency. Therefore, their output can be defined as the frontier output multiplied by an inefficiency term, $\exp(-u_{ijt})$:

$$Y_{ijt} = Y_{ijt}^* \exp(-u_{ijt}) = f(X_{ijt}; \beta) \exp(v_{ijt}) \exp(-u_{ijt}), \qquad (2)$$

where $u_{it} \geq 0$ and is assumed to be i.i.d. as a half-normal and be independent from the noise term, v_{ijt}. The inefficiency term measures the gap between frontier and laggard industries, $Y_{ijt}/Y_{ijt}^* = \exp(-u_{ijt})$. It ranges between 0 and $+\infty$, with the value of 0 identifying a frontier (fully efficient) industry.

The model described in Eq. (2) has three relevant features (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 inclusion of the error term, v_{ijt}, makes Y_{ijt} a *stochastic* production frontier, suitable for statistical inference and hypothesis testing. This distinguishes our model from the non-parametric frontier approach employed, among others, by Färe et al. (1994) and Kumar and Russell (2002). Third, by using the SFM, we can identify contributions of technical change and efficiency change to TFP performance, and assess their importance to explain the observed pattern of productivity growth.

The frontier is specified as a translog production function, expressed in a log-linear form (logged variables in lower case letters):

$$y_{ijt} = \sum_n \beta_n \cdot (x_{nijt}) + \frac{1}{2}\sum\nolimits_n \sum\nolimits_p \beta_{np} \cdot (x_{nijt}x_{pijt}) + tfp_{ijt} + \alpha_i + \mu_j + v_{it} \qquad (3)$$

[3] In our setting each industry is compared with the set of industry-country pairs that lies on the frontier. Conversely, in the empirical works referring to the mainstream productivity literature, the frontier is unique and defined as the industry-country pair with the highest TFP level (see, Griffith et al. 2004 and Minniti and Venturini, 2017, among others).

Following Stiroh (2002a) and O'Mahony and Vecchi (2005) 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 also includes two sets of intercepts, α_i and μ_j, to control for unobserved (time-invariant) heterogeneity at industry and country level. v_{ijt} is a symmetric random disturbance capturing all unknown factors that can affect output production but are not accounted for in our specification.

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 a standard time trend t, or investment-specific, as measured by the interaction between $R\&D_{ijt}$ or ICT_{ijt} and the time trend ($t \cdot R\&D_{ijt}$ and $t \cdot ICT_{ijt}$). Lastly, a third component accounts for the distance from the production boundary; this is our measure of inefficiency (u_{ijt}). Hence, TFP can be specified as follows:

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

The production frontier is obtained by plugging eq. (4) into eq. (3). Our framework of analysis also recognises that $R\&D_{ijt}$ and ICT_{ijt} may affect how efficiently firms use factor inputs. To identify this effect, we parameterize the variance of the inefficiency distribution as a function of ICT and R&D capital stocks (Caudill and Ford, 1993):

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

Our setting extends the main framework used in earlier works by allowing ICT to impact on TFP via the investment-specific route (β_{ict} in the production frontier, eq. 1), via investment-specific technical change (ρ_1 in eq. 4) and via the efficiency route (δ_1 in eq. 5). At the same time, we also account for the impact of R&D, which operates via a within-industry spillover impact on TFP (θ), an effect on investment-specific technical change (ρ_2) and on efficiency (δ_2).[4]

2.2 Estimation method and a preliminary test on the adequacy of SFM

The parameters contained in the production frontier, ($\boldsymbol{\beta}, \theta, \boldsymbol{\rho}, \alpha_i, \mu_j$), and those in the inefficiency equations, ($\boldsymbol{\delta}$) are jointly estimated via maximum likelihood (ML) with a one-step procedure.[5] In this framework of analysis, the error term (ε_{ijt}) is asymmetric as it is equal to the sum of the two components discussed above, i.e. the unobserved random term and the inefficiency component ($\varepsilon_{ijt} = v_{ijt} - u_{ijt}$). The distributional assumptions on $v_{ijt} \sim iid\ N(0, \sigma_v^2)$ and $u_{ijt} \sim iid\ N^+\left(0, \sigma_{u_{ijt}}^2\right)$ are necessary to separate technical inefficiency from noise (see Kumbhakar and Lovell, 2000; pp. 75-77).

A convenient parametrization is to set ${\sigma_{ijt}}^2 = (\sigma_{u_{ijt}}^2 + \sigma_v^2)$ and $\lambda = \sigma_{u_{ijt}}/\sigma_v$ (Greene 2008, pp. 117). λ provides an indication of the relative contribution of u_{ijt} and v_{ijt} to ε_{ijt} and a likelihood ratio test of the null hypothesis that $\lambda = 0$ corresponds to testing that there is no inefficiency in our model. Hence, rejection of the null implies that SFM has to be preferred to a non-frontier production function. Our data strongly support the adoption of a frontier model (see raw 3, Table A.2 in the Appendix).[6]

An issue that has recently been addressed in the estimation of stochastic frontier models is the presence of unknown common factors that can create strong dependency across units (Mastromarco et al. 2016). Examples of such unobserved factors include global shocks, such as

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[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 brings to biased estimates of technology parameters (see Kumbhakar and Lovell, 2000; pp. 272-3).

[5] This procedure outperforms the two-step methodology mostly used in the literature. The latter consists of first estimating inefficiency scores from a baseline production frontier, and then regressing these values on a set of additional covariates. The two-step procedure has been shown to yield biased estimates of the (in)efficiency parameters in presence of omitted variables in the first-step estimation (Wang and Schmidt, 2002).

[6] 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).

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. However, if such un-accounted factors are correlated with regressors, estimates can be biased. Controls for cross-sectional dependence are now routinely included in panel data analyses, both in pooled or mean group estimators. Here, to consistently estimate input elasticities and the impact of the determinants of technical efficiency, we adopt the Pooled Common Correlated Effects estimator (CCE), following Pesaran (2006). We therefore approximate the effect of unobserved common factors with the cross-sectional averages of dependent and independent variables.

3. Data

The analysis is carried out using industry-level data, extracted from the EUKLEMS database (O'Mahony and Timmer 2009). 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.[7] 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.

Industry output is measured in terms of value added. Labour input is the number of hours worked. We distinguish between two components of fixed capital, stock of ICT assets (computers, communication equipment and software) and non-ICT assets (structures, transport equipment and other equipment). These stocks are built from annual investment by means of the perpetual inventory method and adopting an asset-specific rate of geometric depreciation. As a measure of

[7] 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).

R&D input, we use the cumulative value of industry research expenses; this stock is constructed with the same method adopted for physical assets but imposing a standard depreciation rate of 15%.

In our analysis, all monetary variables are expressed at constant prices and in purchasing power parities of 1997 (PPP) on the basis of industry output PPP deflator developed by Inklaar and Timmer (2008). Appendix Table A.1 presents summary statistics for the overall sample.

4. Results

4.1. Benchmark results

Table 1 presents our first set of results. The table is divided into three panels. Panel A presents the estimation of the production function coefficients.[8] Panel B reports the impact estimated for inefficiency determinants, whereas panel C displays estimates of the standard deviation of the normally distributed error term.

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 over two distinct time intervals, the pre-1995 and the post-1995 period. This year is considered the watershed for the advent of the information revolution and the setting of knowledge-based societies (Stiroh 2002b). This allows us to check whether there have been changes in the contributions to productivity performance of the different channels over time (namely input accumulation, technical change and technical efficiency).

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.[9]

[8] Inputs and output are normalized by the mean correction (and taken in logs). Hence, first-order coefficients of the translog production function can be interpreted as output elasticities.
[9] Reviewing a large number of empirical studies, Kretschmer (2012) concludes that a 10% increase in ICT increases productivity growth by approximately 0.5%.

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 o investment-specific technical change discussed above.

Table 1. Benchmark model

	(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 (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(σ_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

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.

The specification in col. (3) – our benchmark specification - further extends our model to account for the impact of R&D and ICT on technical inefficiency. As shown by the negative coefficients in Panel B of Table 1, both R&D and ICT reduce technical inefficiency. This result points to a better managing of production inputs in those industries that invest in technologically advanced assets. Furthermore, when including this additional 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). Hence, these findings indicate that failing to account for the efficiency impact of technologically advanced assets may yield biased estimates for their direct effects on productivity.

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 decreases productivity in the first part of our sample period, with an elasticity of -0.065, while the effect becomes positive from 1995 onwards. Between 1995 and 2007, a 1% increase in ICT increases output by 0.07%. An opposite effect is estimated for the ICT-specific technical change, which is positive before 1995 and negative afterwards. This suggests that in the early stages of diffusion of new technology, firms could easily gain from outward movements of the production frontier induced by these investments. Once the new technology diffuses, and in the absence of significant frontier movements, firms start investing in new digital assets. In the latter phase, 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.

A crucial insight is that the efficiency impact of ICT and R&D is always significantly positive and increasing over time (especially for ICT). In other words, efficiency gains associated with investments in technologically advanced assets appear to have a broad scope, offering stable productivity gains which are not linked to a particular stage of technology adoption/diffusion or industry life-cycle (Bos et al. 2013).

4.2 Heterogeneous frontiers

In the previous section, we estimated the SFM imposing a common frontier across all industries. In this section, we relax this assumption and allow all coefficients to vary across industry groups. Since the intensity of usage of ICT and R&D, and possibly returns related to these factors, are likely to differ with the technological requirements of production, we distinguish our sample into two groupings. The first group gathers 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).[10]

The results for the full specification by industry groupings are reported in Table 2. The impact of R&D capital on the production frontier does not differ much between high-tech and low-tech industries, whilst ICT capital is positive and significant in high-tech sectors and insignificant in low-tech industries. 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 supports the idea that embodied technology is an important driver for productivity upgrades in industries that most intensively invest in technologically advanced assets (intangible and tangible) or, put differently, that these investments need to overcome a critical threshold to effectively generate investment-specific technical change (i.e. outward movement of the frontier).

Results for the inefficiency equation reveal that ICT investments are always associated with a decrease in inefficiency, although the effect is much stronger in the high-tech sector. Conversely, R&D capital is negatively related to efficiency levels in high-tech productions while it increases productive efficiency in low-tech industries. This finding would suggest that more innovative industries are less focused on the reduction of technical inefficiency as they enjoy a competitive

[10] See the Eurostat web-page: http://ec.europa.eu/eurostat/cache/metadata/Annexes/htec_esms_an2.pdf

edge from R&D-induced frontier movements. A related explanation is that R&D activities lead to the introduction of new products and processes which, within an industry, shift the production frontier outward, amplifying the levels of inefficiency below the frontier. This finding is consistent with the firm-level evidence in Andrews et al. (2015), where the increasingly fiercer competition between global frontier firms, mostly active in high-tech sectors, generates a wider productivity dispersion among laggards. In low-tech industries, on the other hand, R&D activities are associated with higher levels of production efficiency as innovations are likely to be incremental and more derivative, or directed towards softer innovations (organizational, managerial, etc.). This allows companies to refine and update production tasks and organizational practices. This finding is consistent with the analysis in Bos et al. (2013).

Another interesting result is that, in the high-tech sector, the role of ICT in reducing inefficiencies goes in the opposite direction to that played by R&D.[11] This suggests that the introduction of organizational changes related to the adoption of ICT has been particularly beneficial for this group of industries. Our results also support the general idea that productivity growth and technological change are not an unintentional by-product of production but a purposeful activity (Acemoglu and Zilibotti 2001), and that investments in R&D are directed towards different technologies depending on relative profitability. In high-tech industries, it is more profitable to direct R&D efforts towards the creation of breakthrough innovations, while in low-tech industries, where the probability of inventing new products is more limited, R&D could be directed towards improving efficiency.

[11] The correlation coefficient between ICT and R&D in the high-tech sector is 0.20 for the overall sample. This rules out any multicollinearity issue.

Table 2. Heterogeneous production frontiers

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

5. Extensions

5.1 Inter-industry spillovers

One may question that the effect of R&D or ICT is incorrectly estimated because these variables capture knowledge transfers or productivity spillovers across industries and countries. In other words, 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. Here we control for such misspecification problems by including a measure of inter-industry R&D and ICT spillovers (*PR&D* and *PICT* respectively) as additional determinants of TFP. We therefore re-write equation (4) as follows:

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

Equation (4.b) requires the computation of *spillover pool* proxies, i.e. variables capturing the amount 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 represented by the shares of intermediate input purchases over total intermediate input expenditure of the purchasing industry. For R&D, our spillover pool variable is defined as:

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

where i denotes industries and j denotes countries. I_{ij} identifies inter-industry purchases of intermediate inputs made at home or abroad. These are 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:

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

As discussed in Section 2.2, our model specification controls for CSD 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.

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

Table 3. 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***	0.472***	0.454***	0.455***	0.584***	0.592***
	(0.011)	(0.011)	(0.011)	(0.011)	(0.016)	(0.016)
Ln(Non-ICT)	0.218***	0.225***	0.240***	0.242***	0.254***	0.216***
	(0.008)	(0.008)	(0.008)	(0.008)	(0.012)	(0.012)
Ln(ICT)	0.080***	0.076***	0.061***	0.060***	-0.072***	0.077***
	(0.006)	(0.006)	(0.006)	(0.006)	(0.010)	(0.008)
R&D	0.153***	0.151***	0.156***	0.155***	0.178***	0.141***
	(0.002)	(0.002)	(0.002)	(0.002)	(0.003)	0.003)
Ln(PR&D)		0.056***		0.0240***	0.048***	0.011
		(0.006)		(0.006)	(0.008)	(0.009)
Ln(PICT)			0.177***	0.169***	0.144***	0.089***
			(0.008)	(0.008)	(0.013)	(0.014)
Time trend (t)	-0.026*	-0.015	-0.032**	-0.025	-0.059	0.000
	(0.014)	(0.019)	(0.014)	(0.019)	(0.063)	(0.000)
t × ICT (in mill. $)	-0.002	0.003	-0.011	-0.0081	2.525***	-0.052***
	(0.007)	(0.007)	(0.007)	(0.007)	(0.277)	(0.009)
t × R&D (in mill. $)	0.124***	0.131***	0.120***	0.123***	0.141***	0.097***
	(0.003)	(0.003)	(0.003)	(0.003)	(0.010)	(0.004)
Constant	1.326**	0.871	0.963	0.747	2,035	0.449
	(0.558)	(0.697)	(0.600)	(0.702)	(2.651)	(4.645)
Panel B: Inefficiency equation. Dependent variable: $ln(\sigma_{u,ijt}^2)$ (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)
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: $ln(\sigma_v^2)$ (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 3 reports our results for the extended specification. The first column reproduces the coefficient estimates for the benchmark specification (Table 1, col. 3) for comparison purposes, while columns (2) – (6) include our proxies for inter-industry spillovers. These are considered separately in columns (2) and (3), whilst in column (4) we include both variables 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 both proxies are included 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.[13] 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). A similar pattern is observed in columns (5) and (6), where we split the sample into pre- and post-1995 periods. In the later time frame, the inter-industry R&D spillover is no longer statistically significant. This may be due to the increasing difficulty of R&D to turn into innovation output and the reduced potential for technology transfers (Segerstrom 1998, Venturini 2012, Bloom et al. 2017). Conversely, for ICT the inter-industry spillover effect plays an important in the role overall period (col. 4), although the effect is lower after 1995.[14]

5.2 C*omplementarities between ICT and R&D*

So far, we have allowed for both the impact of R&D and ICT on productivity and technical efficiency, and we have seen that they both play an important role. To further investigate the complementarities between the two investment types, we extend our specification and include an interaction term in the efficiency component of the model. Table 4 presents only 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). Results in Table 5 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. However, this does not affect the overall conclusion of our study about the importance of accounting for ICT and R&D and the complex way in which they contribute to productivity performance.

[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). These results are omitted for sake of brevity.
[14] See Section A.1 of the Appendix for an extended assessment of the sensitivity of the results to the modelling of CSD.

Table 4. 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*** (0.010)	-0.140*** (0.011)	-0.147*** (0.011)
Ln(R&D)	-0.230*** (0.009)	-0.144*** (0.011)	-0.157*** (0.011)
Ln(ICT) × Ln(R&D)		-0.021*** (0.002)	-0.019*** (0.002)
Constant	0.657*** (0.046)	0.469*** (0.046)	0.517*** (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 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. The computation is carried out using the results for the extended model (eq. 4.b), which includes all transmission mechanisms. The derivation of the respective components is shown in Section A.2 of the Appendix.

Table 5 reports our results. Our model predicts a positive output growth throughout the period, which has been driven to a large extent by TFP growth, and secondarily to factor accumulation, particularly the accumulation of ICT and non-ICT capital. In fact, the contribution of labour accumulation is negative (-0.27%).

Table 5. 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%**
Components of 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 5 shows that R&D and ICT contribute to TFP growth via the efficiency channel by a 0.9% and 0.7%, respectively. Although small, these contributions are positive and statistically significant. Efficiency change overall explains approximately 1% of TFP growth (see the full decomposition in Table A.5), a much smaller effect compared to the other channels, consistently to what found in earlier papers (Henry et al. 2009, Bos et al. 2010).

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.

Our analysis has offered a number of important results. 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; 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 also find some evidence of complementarity between R&D and ICT in reducing inefficiencies in production. However, when accounting for industry heterogeneity, we find that whilst ICT has wide positive effects on efficiency across sectors, R&D is associated with larger inefficiency levels in high-tech industries, probably because of the introduction of radical and 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 of developed countries since the early 1970s. The magnitude of the effect appears much larger than found in works using similar data (Mc Morrow 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). We leave this development to future research.

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Appendix

Table A.1. Summary statistics

Variable	Observations	Mean	Standard deviation	Min.	Max.
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

Table A.2 Specification tests

Null hypothesis	**Conditions**	**Chi^2 statistics**	**Critical values (5%)**
Cobb-Douglas	β_{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	$\lambda = 0$	< 0.01	2.71
No common correlated effects	$\delta_n = 0$, for n,p=L, K, ICT and δ_{np}=0, for n,p=L, K, ICT	96.28	19.67
No technical change components	ρ_1=0 & ρ_2=0 & ρ_3=0	1650.00	7.81

Notes: these tests refer to the benchmark specification (Col. 3, Table 1).

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*** (0.011)	0.477*** (0.011)	0.459*** (0.010)
Ln(non-ICT)	0.218*** (0.008)	0.217*** (0.008)	0.241*** (0.008)
Ln(ICT)	0.080*** (0.006)	0.067*** (0.006)	0.048*** (0.006)
Ln(R&D)	0.153*** (0.002)	0.150*** (0.002)	0.152*** (0.002)
Ln(PR&D)			0.028*** (0.006)
Ln(ICT)			0.162*** (0.008)
Time trend (t)	-0.026* (0.014)	-0.026* (0.014)	-0.025 (0.019)
t × ICT (in mill. $)	-0.002 (0.007)	0.010 (0.007)	0.003 (0.007)
t × R&D (in mill. $)	0.124*** (0.003)	0.126*** (0.003)	0.126*** (0.003)
Constant	1.326** (0.558)	1.305** (0.555)	0.737 (0.699)
Panel B: Inefficiency equation. Dependent variable: $ln(\sigma_{u,ijt}^2)$, *(logged standard deviation of the inefficiency distribution)*			
Ln(ICT)	-0.201*** (0.010)	-0.140*** (0.011)	-0.147*** (0.011)
Ln(R&D)	-0.230*** (0.009)	-0.144*** (0.011)	-0.157*** (0.011)
Ln(ICT) x Ln(R&D)		-0.021*** (0.002)	-0.019*** (0.002)
Constant	0.657*** (0.046)	0.469*** (0.046)	0.517*** (0.045)
Panel C: Dependent variable: $ln(\sigma_v^2)$ *(logged standard deviation of normally distributed error term)*			
Constant	-2.138*** (0.014)	-2.138*** (0.014)	-2.159*** (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 1), 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*** (0.011)	0.480*** (0.011)	0.485*** (0.012)	0.509*** (0.010)	0.616*** (0.011)
Ln(non-ICT)	0.218*** (0.008)	0.211*** (0.008)	0.217*** (0.008)	0.211*** (0.007)	0.163*** (0.008)
Ln(ICT)	0.080*** (0.006)	0.080*** (0.006)	0.0790*** (0.006)	0.0346*** (0.005)	0.0632*** (0.006)
Ln(R&D)	0.153*** (0.002)	0.156*** (0.002)	0.159*** (0.003)	0.171*** (0.002)	0.153*** (0.002)
Time trend (t)	-26.21* (14.34)	-1.533** (0.670)	-32.17** (14.25)	3.961*** (0.646)	-26.76** (13.62)
t × ICT (in mill. $)	-0.002 (0.007)	0.002 (0.007)	-0.006 (0.007)	0.031*** (0.007)	-0.020*** (0.007)
t × R&D (in mill. $)	0.124*** (0.003)	0.122*** (0.003)	0.121*** (0.003)	0.122*** (0.003)	0.093*** (0.003)
Constant	1.326** (0.558)	0.790*** (0.029)	0.813 (0.665)	0.478*** (0.027)	1.056 (1.680)
Panel B: Inefficiency equation. Dependent variable: ln($\sigma_{u,ijt}^2$) *(logged standard deviation of the inefficiency distribution)*					
Ln(ICT)	-0.201*** (0.010)	-0.187*** (0.010)	-0.175*** (0.010)	-0.544*** (0.017)	-0.205*** (0.009)
Ln(R&D)	-0.230*** (0.009)	-0.211*** (0.009)	-0.203*** (0.009)	-0.264*** (0.011)	-0.255*** (0.009)
Constant	0.657*** (0.046)	-0.368 (1.916)	-4.705* (2.813)	2.548 (2.369)	0.856*** (0.045)
Panel C: Dependent variable: ln(σ_v^2) *(logged standard deviation of normally distributed error term)*					
Constant	-2.138*** (0.014)	-2.154*** (0.014)	-2.166*** (0.015)	-2.243*** (0.012)	-2.358*** (0.016)
Industry dummies	Yes	Yes	Yes	Yes	Yes
Country dummies	Yes	Yes	Yes	Yes	Yes
Common Correlated Effects	Frontier	Efficiency	Frontier+ Efficiency	Frontier	Frontier
Common Correlated Effects (parameters)	Common	Common	Common	Country-specific	Industry-specific
Observations	6332	6332	6332	6332	6332
Log-likelihood	-21952.0	-21939.4	-21863.3	-19006.8	-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), $EC = -\frac{\partial \mathrm{u}_{ijt}}{\partial \mathrm{t}} = -(u_{ijt} - u_{ijt-1})$

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:

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

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

$$\dot{y}_{ijt} =$$

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

$$\underbrace{(\theta_3 \cdot PIC\dot{T}_{\iota jt})}_{inter-industry\ ICT\ spillover} \tag{9}$$

[15] Output elasticity of each input n is defined as $\gamma_{n,ijt} = \frac{\partial y_{ijt}}{\partial x_{nijt}} = \beta_n + (\beta_{nn} \cdot x_{n,ijt}) + \sum_{p \neq n} \beta_{np} \cdot x_{p,ijt}$ 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, the marginal effect of ICT on $E[u_{ijt} | \ln ICT_{ijt}, \ln R\&D_{ijt}]$ is

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

And the marginal effect of R&D is:

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

Source: Kumbhakar S. C., Parmeter C. F., Zlenyuk V. (2017), "Stochastic Frontier Analysis: Foundations and Advances", Working Papers 2017-10, University of Miami, Department of Economics.

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%**
Labor 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%