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Small is big in ICT: The impact of R&D on productivity

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ABSTRACT

We examine the contribution of R&D to firm productivity in a large panel of European firms and study its variation with the age, size, and sub-sector of firms. We find that R&D capital in ICT firms has a larger effect on revenue when compared to non-ICT firms. At the firm level, our results suggest that, surprisingly, smaller and older ICT firms benefit the most from R&D. Small but mature ICT firms are likely to dominate market niches, and small size may enable them to be flexible and adaptable which helps them respond to technological opportunities to develop innovative products and services. This has important implications for public policy based upon firm age.

1. Introduction

The slowdown in productivity growth is central to the political and economic debates of our times. Some have attributed the slowdown to sectorial effects, such as increased shares of low-growth sectors (Baqaee & Farhi, 2017), resource misallocation within sectors (Calligaris, Del Gatto, Hassan, Ottaviano, & Schivardi, 2018), and increased concentration within and across industries (Goldin, Koutroumpis, Lafond, Rochowicz, & Winkler, 2018). Others have identified technological effects, such as the lack of significant technological innovations compared to the past (Gordon, 2000), the lag in the adoption of transformative technologies (Brynjolfsson, Rock, & Syverson, 2018), and an increasing mismatch in skills (Acemoglu & Zilibotti, 2001; Daveri & Maliranta, 2007). Others have considered firm level effects, such as the rise of Zombie firms (Adalet McGowan, Andrews, & Millot, 2018) and the rise of superstar firms (Andrews, Criscuolo, & Gal, 2015). Still yet others have identified policy-induced frictions (Andrews & Cingano, 2014).

However, while these links suggest that the relationship between R&D and productivity has been thoroughly analyzed,[2] less is known about the differences in R&D and productivity across sectors, and particularly of the ICT sector. R&D effectiveness in Information and Communication Technologies (ICTs) innovation directly influences the rate of digital transformation of the economy, improving firm productivity across industries and contributing to the economic growth of nations (Bloom, Sadun, & Ven Reenen, 2012; Brynjolfsson & Hitt, 2003; Hitt & Brynjolfsson, 1996). Furthermore, given that entrepreneurship is in a 30-year decline in the United States, despite academic and policy efforts to the contrary (Decker, Haltiwanger, Jarmin, & Miranda, 2015), ICT-based high-

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[2] See Griliches (2007) for a review.

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technology startups are viewed as the holy grail of economic development. As such, investigating the role of age and size in the context of R&D and productivity is particularly relevant for small and young ICT firms.

ICT is often included in production functions as it affects both the generation of firm output and the creation of innovative ideas (Hall, Lotti, & Mairesse, 2013; Kleis, Chwelos, Ramirez, & Cockburn, 2012). As a "general purpose technology" it can be applied in many contexts (Bresnahan & Trajtenberg, 1995), and as an "invention machine" it facilitates invention of new products and services in other sectors (Koutroumpis, Leiponen, & Thomas, 2017a, b). ICTs appear to interact and complement R&D investments leading to significant joint effects on firm performance (Bardhan, Krishnan, & Lin, 2013): an increase in ICT investment is associated with an increase in R&D output controlling for innovation-related spending (Kleis et al., 2012). However, there are few, if any, studies focusing on the relationship between R&D and productivity in ICT firms themselves.

We view R&D and productivity through the notion of technological opportunities (Klevorick, Levin, Nelson, & Winter 1995). Technological opportunities comprise the set of possible avenues for technological advancement, and as ICT industries have a close dependence on scientific activity and rapid scientific progress, there is a rapidly moving technological trajectory (Dosi, 1982) which refreshes the available technological opportunities. Furthermore, spatial and technological proximity among innovators in technology "hotspots", industrial parks, universities, and technology incubators has accelerated technology development and adoption within ICT industries (Adams & Jaffe, 1996; Tambe & Hitt, 2014). Indeed, knowledge spillovers between ICT firms have attracted considerable policy interest in the economic impact of R&D (Ezell & Andes, 2010), because these technologies make a vital contribution to knowledge-based economies.

In this paper, we compare technological opportunities faced by ICT and non-ICT firms using the distribution of returns to R&D as a measure of opportunity (Klevorick et al., 1995). We define an ICT firm as a firm that produces ICT products or services, even if the firm is classified under different industry classifications. We use a large panel of firms from Germany, France, Sweden and the United Kingdom for the period 2004–2013 to estimate the effect of R&D capital on firm productivity. First, we use a lagged Cobb-Douglas production function to estimate R&D elasticity comparing industry, age, and size effects. We test the robustness and consistency of our results using instrumental variable and quantile regressions. As a final robustness test, we apply the performance index framework of Klette (1996) that enhances the standard Cobb-Douglas approach.

We break down the productivity impact of R&D capital by the age and size of firms. In particular, the years of experience in a sector and the knowledge capital acquired can significantly affect management practices, recruitment priorities, and strategic decisions, and hence performance (Herriott, Levinthal, & March 1985). Similarly, the size of the firm is linked to the effect of technology diffusion within firms and their private returns (Cohen, 1995; Cohen & Klepper, 1996). However, the degree to which R&D drives the performance of entrepreneurial, i.e., small and young firms, as opposed to either older or larger establishments, has rarely been examined (for an exception see Peters, Roberts, Vuong, & Fryges, 2017).

Our analysis of the moderating effects of industry, firm size, and firm age suggests that R&D capital in ICT firms has a larger impact on revenue when compared to non-ICT firms. Although the R&D impact is significantly larger for small ICT firms relative to non-ICT firms, the difference is the greatest for older small firms. We interpret our findings through the notion of "technological opportunism" (Mishra & Agarwal, 2010; Srinivasan, Lilien, & Rangaswamy, 2002): while small firms can better sense and respond to technological opportunities and market shifts, and hence have greater flexibility and adaptability in their innovation and managerial processes, this does not seem to necessitate youth. More experienced small firms that are likely to dominate market niches are able to make the most of their investments and exhibit greater capabilities of technological opportunism.

Our results suggest that policy makers concerned with innovation-driven growth should target R&D incentives at ICT firms. Not only our finding underlines the impressive contribution that small research budgets can have in this technology sector (Bronzini & Piselli, 2016; Criscuolo, Martin, Overman, & Van Reenen, 2012; OECD, 2015), but it suggests that current policy initiatives focused on younger firms need to be re-evaluated. For instance, at the European and national levels, much of the current policy interest and academic guidance (see, for instance Veugelers & Cincera, 2010) is based upon the observation that Europe has fewer startup innovators than the US, in relative terms. Our results suggest that, in the ICT sector at least, policies should not exclude older firms.

The paper is organized as follows. In Section 2 we review the existing literature concerning technological opportunities, R&D investment, firm performance, and the effects of firm size and age. Section 3 introduces the econometric specification used for the analysis. In Section 4 we describe the data sources and methods used to analyze them; Section 5 presents the main results and several robustness analyses, including the distribution of the effects using quantile regressions, and instrumental variable models to assess the causality of our findings. In Section 6 we discuss the findings, implications for policy, and conclude.

2. Technological opportunities, R&D, and firm performance

Technological opportunities comprise the set of possible avenues for technological advancement and are an important aspect of the technological regime within which innovation and R&D occur (Klevorick et al., 1995; Revilla & Fernández, 2012). Technological opportunities are used when innovation occurs, that is, when a new technology is launched and commercialized, and hence can be measured as the distribution of returns to R&D (Klevorick et al., 1995). New or improved products and services will expand sales through enhanced demand, whereas new or improved processes allow firms to compete more effectively and thereby gain market share. Technological opportunities are not finite as they are replenished through advances in scientific understanding, technological progress in enabling technologies originating outside the industry, and even positive feedback from the technology itself. The ICT industry is of particular interest. In their comparative study of the manufacturing sector, Klevorick et al. (1995) found that the ICT industry, especially electronic components, had the greatest sources of opportunity renewal. At that time, semiconductors and electrical equipment had particularly high opportunities for innovation.

The study of technological opportunities is related to a larger literature regarding the effects of R&D on economic performance of the firm. R&D is traditionally viewed as an input into knowledge creation that might eventually lead to new technologies or products (Griliches, 1990, 1998; Hausman, Hall, & Griliches, 1984). Early studies found an effect of R&D on firm output, evident both directly as a component of firms' production functions and indirectly via total factor productivity (Mansfield, 1980). Subsequent studies have shown that R&D has a positive effect on the value of firms in the capital markets (Hall & Oriani, 2006) and their innovation performance (Mairesse & Mohnen, 2004).

Firm age and size influence the ability of firms to take advantage of technological opportunities through R&D. Firm size has been found to have a positive effect on the level of R&D investment (Acs & Audretsch, 1988; Czarnitzki & Hottenrott, 2011), however, evidence for scale economies in R&D is mixed (Cohen & Klepper, 1996). It has been suggested that smaller firms experience a performance boost from R&D investment where there are abundant technological opportunities (Revilla & Fernández, 2012). Other studies have found that larger, older and more productive firms have higher returns to R&D expenditure (Peters et al., 2017).

In terms of the effect of firm age, the empirical findings are also mixed. On the one hand there are learning effects, as firms gain experience and build on previous routines and capabilities, innovate more effectively, and subsequently achieve better firm performance (Sorensen & Stuart, 2000). In particular, older firms are able to accumulate resources, managerial knowledge and the ability to handle uncertainty (Herriott et al., 1985; Levitt & March 1988), such that previous R&D experience for older firms results in more persistent and less erratic innovation (García-Quevedo, Pellegrino, & Vivarelli, 2014). With age firms can accumulate reputations and beneficial market positions, which facilitate relationships with suppliers, customers and potential collaborators, leading to improved performance. Furthermore, recent research has also found that successful entrepreneurs themselves are middle-aged, not young, and that prior experience in a specific industry predicts greater entrepreneurial success (Azoulay, Jones, Kim, & Miranda, 2018).

On the other hand, age may also have negative effects, including the obsolescence of the firms' knowledge base, as the processes of search become outdated and not well-suited to the current technological landscape (Sorensen & Stuart, 2000). Older firms may also experience organizational inertia that hinders learning (Majumdar, 1997). Aligned with these ideas, firm age is found to be negatively related to the quality of technical innovations, and this effect is greater in rapidly progressing technology areas (Balasubramanian & Lee, 2008). Others have provided evidence that the oldest firms tend to show lower probabilities of successful innovation (Huergo & Jaumandreu, 2004), although R&D investment by younger firms appears to be significantly more risky than R&D investment by more mature firms (Coad, Segarra, & Teruel, 2016).

A small number of studies have considered the relationship between R&D and revenue, and the results are mixed. Some studies identified a positive effect of R&D capital on revenue growth (Del Monte & Papagni, 2003), while more recently, Coad et al. (2016) found that R&D was positively associated with the growth of the number of employees and productivity, but not revenue. Other research has explored the effect of innovation (variously measured) on revenue performance, e.g. Scherer (1965) and Geroski and Machin (1992), and most recently Coad and Rao (2008), who found that innovation matters for revenue growth only for high-growth firms. However, none of these studies have focused on the effect of R&D capital on revenue performance in the ICT sector.

In this paper, we compare the returns to R&D capital in terms of revenue performance across industries and types of firms to complement the view that ICT drives innovation and productivity in other sectors. We aim for a better understanding of the internal technological dynamics and impact of the ICT sector itself.

3. Econometric specification

Knowledge created through R&D investments is viewed as a form of capital. Unlike tangible forms of capital, knowledge can be used by more than one firm at the same time and is not perfectly excludable. Therefore, R&D investments are assumed to generate internal returns, as firms improve their own products and processes to increase profits, and spillovers that involve unintended positive effects on rivals. In turn, firms may also benefit from rivals' R&D capital. There are thus both internal and external R&D inputs which affect firm performance (Cohen & Levinthal, 1989; Romer, 1994).[3] In this paper we focus on the private returns of research investments.

We assume that R&D creates a stock of knowledge that yields returns in the future. The knowledge capital stock can be constructed using the perpetual inventory method with a single or variable depreciation rates:

$$\mathrm{K}_{it} = (1 - \delta_{ct})K_{i,t-1} + R_{it} \tag{1}$$

where K_{it} is the knowledge stock of firm i at time t, R_{it} is the real investment of firm i in R&D at time t, and δ_{ct} is a depreciation rate of industry c at time t. Hall and Mairesse (1995) show that the initial stock of R&D can be estimated by the following formula, where g_c is the growth rate of R&D in the period of study (assuming constant growth) and δ_c is the depreciation rate (constant for each -firm):

$$\mathrm{K}_{it} = \frac{R_{it}}{g_c + \delta_c} \tag{2}$$

We use (2) to generate estimates of the initial knowledge stock in our analysis.

We first start our analysis with the Cobb-Douglas production function. We assume that R&D activity primarily affects firm output. To measure the effects of R&D investments on revenue we utilize a firm-level production function framework:

[3] There is extensive literature into what constitutes a production spillover, see Bresnahan (1986) and Keller (1998).

$$\log(Revenue_{ijt}) = b_1 \log(K_{ijt}) + b_2 \log(C_{ijt}) + b_3 \log(L_{ijt}) + b_4 \log(M_{ijt}) + X_{ijtn} + \varepsilon_{ijt} \quad (3)$$

where $Revenue_{ijt}$ is the reported revenue for company i in country j at year t, K_{ijt} represents the knowledge capital as measured by the investment in R&D in thousand Euros, C_{ijt} are the total assets,[4] L_{ijt} is the total employment, M_{ijt} are the intermediate inputs and X_{ijtn} is a vector of country j, year t and NACE technology classification n fixed effects, including industry-year dummies and country-year dummies.

4. Dataset

We analyze 9474 firms in Germany, France, Sweden and the United Kingdom that report R&D activity for at least three of the years in the ten-year period 2004–2013. Our data source is the Orbis/Amadeus dataset.[5] We restrict our sample to Germany, France, Sweden and the United Kingdom due to poor data availability for other European countries.[6] We combine our data with OECD statistics for the same period on country and sub-industry level duties and taxes, and capital and labor shares.

Our sample contains 740 firms with the European Union's NACE 2.0 ICT industry classifications that report R&D investment.[7] We further expand this ICT group by applying a pattern matching algorithm to the detailed firm descriptions provided by Orbis/Amadeus. We include as ICT firms those that have in their description the following words: communication, telecommunication, electronics, information, or ICT. This expands the ICT group to 558 firms.[8]

To compare the effect of R&D capital on different types of firms, we create indicators for ICT vs. non-ICT firms; small and large firms; and young and old firms. We base our size and age thresholds upon the OECD classifications, where companies with fewer than 100 employees are considered small, and firms with less than 10 years since incorporation are considered young (OECD, 2013). Table 1 presents the summary statistics, listing the number of observations, mean, standard deviation, minimum and maximum of the full sample, as well as for the sub-samples consisting of small, young and ICT firms.

The fixed effects specification of (3) is prone to estimation biases because of the endogenous choice of inputs. For example, a firm may anticipate demand growth in their market and decide to invest in R&D projects to capitalize on the expansion, or a firm may have unobserved skills that enhance their returns to R&D. Hall and Mairesse (1995), Klette (1996), Griffith, Harrison, and Van Reenen (2006) and others have shown that the use of lags can offset endogeneity biases. However, under autocorrelation, linear models using a lagged dependent variable tend to produce downward-biased coefficient estimates of (other) explanatory variables. Nevertheless, Keele and Kelly (2006) argue that if the model truly is dynamic, it is better to include a lagged dependent variable than to omit it—more severe biases are caused by omitting it. Standard errors may also be deflated in lagged dependent variable models with autocorrelation (Beck & Katz, 1997). We present our core estimates with current and lagged dependent and independent variables and complement our analyses with a distance-based instrumental variable and quantile estimations.

While the results need to be interpreted as descriptive due to potentially remaining estimation biases, we primarily rely on comparative analysis between different types of firms. We have little reason to expect that the results are differently biased for different types of firms, and therefore, we expect to identify the differences across firm types reasonably consistently. We also considered GMM dynamic panel data methods (cf. Arellano & Bover, 1995; Blundell & Bond, 1998) that utilize lagged levels and differences as instruments. However, they generate unreliable estimates for our large panel with heterogeneous and persistent data. Therefore, our preferred analyses rely on the fixed effects method with lagged variables to control for potential reverse causality and unobserved heterogeneity.

5. Results

Table 2 presents the results of our analyses for the R&D elasticity of revenue controlling for other inputs into the production function (as specified in equation (3)). For the calculation of the initial R&D capital we use the firm-specific R&D growth rate and a depreciation rate of 15%.[9] Our results hold in all cases.

First, we observe that the coefficients (for columns 1–5) are aligned with our expectations as the current fixed assets, employment and intermediates have positive and significant effects. R&D is a significant explanatory factor in specification (1), but when we add the lagged dependent variable in column (2), the coefficient of R&D may be biased down. Therefore, we view our results including lagged dependent variables as a lower bound for the R&D effect rather than significantly inflated due to endogeneity. We also find no

[4] In the Orbis/Amadeus dataset, total assets is the sum of fixed assets (which comprise intangible, tangible and other fixed assets) and current fixed assets (which comprise stocks, debtors, and cash and cash equivalent).

[5] We use constant 2010 USD in our estimates and thus do not require the use of deflators.

[6] Country level data and analysis which highlights the heterogeneity of R&D availability data within Europe is available from the corresponding author upon request.

[7] The European Union's Nomenclature of Economic Activities (NACE) v2.0 ICT is available at http://ec.europa.eu/eurostat/. Table S1 in the Supplementary Materials details the NACE v2.0 ICT Industry classifications.

[8] The analysis below uses this extended sample. As a robustness check we also ran the results with the NACE v2.0 ICT firms; these do not demonstrate any significant changes to our results.

[9] We use two alternative R&D capital estimates for robustness: the first uses a depreciation rate of 15% and a growth rate of 5% (as used in Hall & Mairesse, 1995), and the second uses a higher depreciation rate of 25% and a growth rate of 5% (obtained by Pakes & Schankerman, 1984). These alternative estimations of R&D capital can be found in the Supplementary Materials (Tables S2 and S3).

Table 1
Descriptive Statistics by firm for each [Small/Young/ICT] cluster.

	Observations	Mean	Std. Dev.	Min	Max
All					
Revenue (th. Eur)	67,414	537,719	4,900,563	0	297,000,000
Assets (th. Eur)	67,414	746,154	6,691,305	0	268,000,000
Employment	67,414	2165	17,319	0	648,254
R&D (th. Eur)	67,414	12,273	142,356	0	5,649,000
Small					
Revenue (th. Eur)	42,558	12,916	67,713	0	4,217,760
Assets (th. Eur)	42,558	29,575	155,897	0	6,197,609
Employment	42,558	26	28	0	99
R&D (th. Eur)	42,558	246	1759	0	98,315
Young					
Revenue (th. Eur)	17,590	198,430	2,180,292	0	151,000,000
Assets (th. Eur)	17,590	319,457	3,479,092	2.162	218,000,000
Employment	17,590	1058	14,904	0	648,254
R&D (th. Eur)	17,590	4683	71,235	0	5,649,000
ICT					
Revenue (th. Eur)	4452	799,137	5,537,157	0	78,400,000
Assets (th. Eur)	4452	1,283,519	10,600,000	0.119	182,000,000
Employment	4452	3241	25,441	0	439,400
R&D (th. Eur)	4452	42,984	328,625	0	5,155,000

evidence of lagged variables depressing standard errors (standard errors for the explanatory variables are larger when we include lagged variables). We therefore prefer the models with lagged variables as they mitigate the effects of reverse causality and show reasonable estimates for labor share (0.29) and capital share (0.66).

The effects of current and lagged R&D capital are small and insignificant in models 1 and 2. When we separately estimate the impact of R&D capital for ICT and non-ICT firms (column 3), we find that the coefficient is significantly positive only for ICT firms, and the difference is statistically significant.[10] If R&D capital is doubled, sales in ICT firms will grow by 9.6% while there is a negligible negative effect for non-ICT firms, suggesting that ICT firms may enjoy significantly greater return on R&D capital than non-ICT firms.

Column 4 in Table 2 separately estimates R&D capital impact depending on firm size and ICT status. Here we find that both large and small ICT firms have the greatest effects; doubling R&D capital yields a 9.0% increase in revenue for large ICT firms, and an even more substantial 10.4% increase for small ICT firms. Small and large non-ICT firms do not have a significant effect. The difference between small ICT versus small non-ICT firms and that between large ICT versus large non-ICT firms are statistically significant. However, the difference between small versus large ICT firms is not statistically significant. Column 5 splits the sample further into young and old, small and large, ICT and non-ICT. Here we find that the largest significant effect is for old and small ICT firms (10.9%), while there are similar significant effects for young and large ICT firms (9.3%) and for old and large ICT firms (8.8%). There is also a significant effect for young and small ICT firms (8.1%). For non-ICT firms, there are no significant effects. The estimates of R&D capital impact for ICT firms are significantly different from those for non-ICT firms, but the differences between coefficients for small versus large and young versus old ICT firms are not statistically different. Taken together, these results suggest that older and smaller ICT firms have the greatest effect on revenues from R&D capital, with lesser effects for non-ICT firms.

We further investigate the effects of firm size. Table 3 presents an analysis of four employment quartiles comparing ICT and non-ICT firms.[11] Here we find the effect of R&D on revenue performance is significant for ICT firms of all sizes, with the effect greater for smaller firms and decreasing as firms get larger. For ICT firms in the lowest employment quartile (fewer than 9 employees) there is an effect of 20.1%, while for ICT firms in the lower-middle quartile (between 9 and 50 employees) there is an effect of 10.3%; there is a 9.0% effect for firms in the upper-middle quartile (between 51 and 209 employees), and 8.8% for firms in the upper quartile (more than 209 employees). The difference in the coefficients between the largest and smallest ICT firms is statistically significant ($Prob > F = 0.0075$).

For non-ICT firms, there is a significant effect (8.3%) for firms in the first quartile (less than 9 employees) decreasing to a smaller significant effect of 1.3% for firms in lower-middle quartile. There is also a small significant negative effect (−1.4%) for firms in the last quartile. These results suggest that ICT firms of all sizes experience a greater performance effect from R&D, and that the returns are the greatest for small ICT firms. If causal, these marginal effects are large and imply that there are residual investment opportunities in ICT.

Table 4 presents analyses by firm age, considering four age quartiles comparing ICT and non-ICT firms.[12] These indicate the strongest significant and positive effect for the oldest ICT firms. In particular, ICT firms in the last age quartile (more than 39 years old) have an effect of 15.5%, whereas the other age quartiles of ICT firms have almost identical effects between 7.9 and 8.1%. The

[10] $F(1, 35690) = 39.23$; $Prob > F = 0.000$.

[11] We break our sample in four employment groups that contain the same number of observations; this effectively breaks our sample into quartiles.

[12] Ages of the first quartile firms are 0–9 years, second quartile 10–19 years, third quartile 20–38 years, and fourth quartile more than 39 years.

Table 2
Impact of R&D on revenue.

Variables	1	2	3	4	5
	log(Revenue)	log(Revenue)	log(Revenue)	log(Revenue)	log(Revenue)
	FE	FE	FE	FE	FE
log(Revenue(t-1))		0.285***	0.284***	0.284***	0.284***
		(0.005)	(0.005)	(0.005)	(0.005)
log(Revenue(t-2))		−0.024***	−0.024***	−0.024***	−0.024***
		(0.004)	(0.004)	(0.004)	(0.004)
log(Assets)	0.554***	0.293***	0.293***	0.293***	0.293***
	(0.006)	(0.008)	(0.008)	(0.008)	(0.008)
log(Assets(t-1))		0.096***	0.097***	0.098***	0.098***
		(0.009)	(0.009)	(0.009)	(0.009)
log (Employment)	0.762***	0.657***	0.655***	0.671***	0.672***
	(0.008)	(0.011)	(0.011)	(0.011)	(0.011)
log (Employment(t-1))		−0.078***	−0.079***	−0.077***	−0.077***
		(0.011)	(0.011)	(0.011)	(0.011)
log(Intermediates)	0.008*	0.012*	0.011*	0.011*	0.011*
	(0.003)	(0.005)	(0.005)	(0.005)	(0.005)
log (R&D)	0.018***	0.002			
	(0.003)	(0.004)			
log (R&D(t-1))		−0.004	−0.004	−0.004	−0.004
		(0.004)	(0.004)	(0.004)	(0.004)
non-ICT firms log(R&D)			−0.002		
			(0.004)		
ICT firms log(R&D)			0.096***		
			(0.016)		
large & non-ICT firms log(R&D)				−0.007	
				(0.004)	
small & non-ICT firms log(R&D)				0.007	
				(0.005)	
large & ICT firms log(R&D)				0.090***	
				(0.017)	
small & ICT firms log(R&D)				0.104***	
				(0.018)	
old & large & non-ICT firms log(R&D)					−0.007
					(0.004)
old & small & non-ICT firms log(R&D)					0.006
					(0.005)
young & large & non-ICT firms log(R&D)					−0.007
					(0.006)
young & small & non-ICT firms log(R&D)					0.010
					(0.007)
old & large & ICT firms log(R&D)					0.088***
					(0.017)
old & small & ICT firms log(R&D)					0.109***
					(0.018)
young & large & ICT firms log(R&D)					0.093***
					(0.020)
young & small & ICT firms log(R&D)					0.081***
					(0.024)
Constant	0.989***	0.934***	0.915***	0.778***	0.777***
	(0.061)	(0.087)	(0.087)	(0.091)	(0.092)
Firm FE	Yes	Yes	Yes	Yes	Yes
Year X NACE FE	Yes	Yes	Yes	Yes	Yes
Year X Country FE	Yes	Yes	Yes	Yes	Yes
Observations	65,923	45,006	45,006	45,006	44,989
Number of firms	9474	9215	9215	9215	9211
R-squared	0.328	0.342	0.342	0.344	0.344

Robust standard errors in parentheses; ***$p < 0.01$, **$p < 0.05$, *$p < 0.1$.

coefficient of the oldest ICT firms is significantly different from all the other groups of firms. For non-ICT firms there are no significant effects. These results suggest, perhaps surprisingly, that smaller and more experienced ICT firms enjoy the greatest effect of R&D capital on revenues.

Table 3
Impact of R&D on output – Employment breakdown.

Variables	1
	log(Revenue)
	FE
log(Revenue(t-1))	0.282***
	(0.005)
log(Revenue(t-2))	−0.024***
	(0.004)
log(Assets)	0.292***
	(0.008)
log(Assets(t-1))	0.097***
	(0.009)
log (Employment)	0.709***
	(0.013)
log (Employment(t-1))	−0.082***
	(0.011)
log (Material)	0.011*
	(0.005)
non-ICT (R&D) firms lower employment quartile	0.083***
	(0.010)
non-ICT (R&D) firms lower middle employment quartile	0.013*
	(0.006)
non-ICT (R&D) firms upper-middle employment quartile	−0.006
	(0.005)
non-ICT (R&D) firms upper employment quartile	−0.014**
	(0.004)
ICT (R&D) firms lower employment quartile	0.201***
	(0.043)
ICT (R&D) firms lower-middle employment quartile	0.103***
	(0.021)
ICT (R&D) firms upper-middle employment quartile	0.090***
	(0.017)
ICT (R&D) firms upper employment quartile	0.088***
	(0.016)
log (R&D(t-1))	−0.004
	(0.004)
Constant	0.936***
	(0.089)
Firm FE	Yes
Year X NACE FE	Yes
Year X Country FE	Yes
Observations	45,006
Number of firms	9215
R-squared	0.345

Robust standard errors in parentheses; ***$p < 0.01$, **$p < 0.05$, *$p < 0.1$.
Notes: We break our sample in four employment groups that contain the same number of observations. This effectively breaks our sample into quartiles: the first includes firms with up to 8 employees, the second from 9 to 50, the third from 51 to 209 and the fourth from 210 and above.

5.1. Robustness tests: distance-based instrumental variable

To assess the possibility of reverse causality running from revenue to R&D capital, we introduce an instrument that directly affects R&D inputs but not firm revenue. The quality and availability of research personnel can influence firms' research inputs, but is unlikely to directly enhance their sales. Firms located close to research centers and universities are likely to be able to recruit high-quality researchers, exchange ideas with the local community and hence enjoy greater R&D productivity. We thus consider a firm's location and its proximity to high quality educational institutions a key variable that affects productivity of and thus investments in R&D. For example, we assume that firms based in Cambridge, Munich, or Lund are more likely to find R&D staff compared to firms based in towns far away from universities or research centers.

To construct this instrument, we combine our dataset with information on university ranking and firms' GIS data. In particular, we first look into global university rankings for the period of study (2004–2013) and focus on the list with the top 100 universities and

Table 4
Impact of R&D on output – Age breakdown.

Variables	1
	log(Revenue)
	FE
log(Revenue(t-1))	0.284**
	(0.005)
log(Revenue(t-2))	−0.024**
	(0.004)
log(Assets)	0.293**
	(0.008)
log(Assets(t-1))	0.097**
	(0.009)
log (Employment)	0.656**
	(0.011)
log (Employment(t-1))	−0.080**
	(0.011)
log (Material)	0.011+
	(0.005)
non-ICT (R&D) firms lower age quartile	0.005
	(0.006)
non-ICT (R&D) firms lower middle age quartile	0.002
	(0.005)
non-ICT (R&D) firms upper-middle age quartile	−0.002
	(0.005)
non-ICT (R&D) firms upper age quartile	−0.007
	(0.005)
ICT (R&D) firms lower age quartile	0.079**
	(0.019)
ICT (R&D) firms lower-middle age quartile	0.081**
	(0.017)
ICT (R&D) firms upper-middle age quartile	0.080**
	(0.019)
ICT (R&D) firms upper age quartile	0.155**
	(0.021)
log (R&D(t-1))	−0.003
	(0.004)
Constant	0.876**
	(0.090)
Firm FE	Yes
Year X NACE FE	Yes
Year X Country FE	Yes
Observations	44,989
Number of firms	9211
R-squared	0.343

Robust standard errors in parentheses; ***$p < 0.01$, **$p < 0.05$, *$p < 0.1$.
Notes: We break our sample in four age groups that contain the same number of observations. This effectively breaks our sample into quartiles: the first includes firms less than 9 years old, the second from 10 to 19 years, the third between 20 and 38 years old and the fourth from 39 years old and above.

colleges, taking the top 100 THE and QS lists for the period 2004–2013.[13] We calculate the straight-line distance of each firm in thousands of kilometers from each of the top 100 universities.[14] Fig. 1 presents the distribution of firms' distances from universities, and reassuringly shows that there is wide heterogeneity in this metric.

Using this instrument, we repeat our analysis. In the first stage, we instrument R&D capital with distance to the nearest top university, and the predicted coefficient for R&D is then used in the second stage. We find that the main effect from R&D remains strong and is now much higher compared to the original estimates. This is not surprising as this type of an IV analysis typically reflects the *local* average treatment effect (cf. Angrist, 2004), not that of the whole population. Nevertheless, our instrument passes the instrument validity, strength, and identification tests that are also reported.

The exogeneity of an instrument is not always easy to assert. Since firms do not choose their location randomly, the observed correlation between R&D and distance from universities could be driven, at least partially, by the correlation between distance and unobserved firm characteristics. For this we include firms fixed effects that can help capture the idiosyncrasies at that level (195 firms

[13] Source: www.universityrankings.ch.
[14] We calculate the distances to universities (with API key) using www.gpsvisualizer.com/geocoder/.

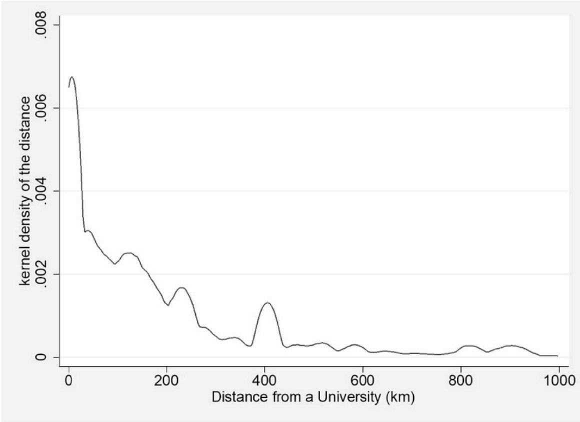

Fig. 1. Distance kernel densities.

in our sample move during the period of study so we can include fixed effects). Moreover, rational firms locate in order to minimize costs, e.g. reduced cost of serving local demand, getting closer to inputs, positive agglomeration externalities, and reduced costs of labor. If best universities are more likely to be located close to major metropolitan areas, university proximity may affect firms' revenues through mechanisms not related to R&D. We assess this by computing the correlation coefficient between a firm's distance from a top university and its presence in a nation's capital. The coefficient has the expected sign (if the firm is located in the capital city, its distance to a top university is lower) but is found to be relatively low at -0.27 thus suggesting a low risk of capital city effects affecting our identification. In other words, there are many top universities that are not located in major metropolitan areas. We further correlate the city level firm counts with the distance from a top university. As firms are more likely to be located in larger cities the firm counts can be considered a proxy of the city size. The resulting correlation is -0.27 again. Last, we also run a further IV model that explicitly accounts for firm location in capital cities. The effect of R&D is not significantly different compared to our baseline case (see Table 5).

Table 5
Robustness checks for the impact of R&D on output (IVs).

Variables	Second Stage	Second Stage
	log(Revenue)	log(Revenue)
	IV	IV
log(R&D)	0.260*	0.387**
	(0.140)	(0.174)
log(Assets)	0.464***	0.433***
	(0.0339)	(0.0418)
log(Employment)	0.484***	0.438***
	(0.0517)	(0.0640)
log(Intermediate)	0.0230***	0.0255***
	(0.00410)	(0.00499)
Capital		0.0433**
		(0.0201)
Constant	2.217***	2.518***
	(0.331)	(0.415)
Firm FE	Yes	Yes
NACE FE	Yes	Yes
Year FE	Yes	Yes
Country FE	Yes	Yes
Large cities FE	No	Yes
Observations	58,708	58,708
R-squared	0.831	0.759

Research expenditures instrumented with research quality (a distance variable indicating the straight-line distance in thousands of km from a high-quality institution in the firm's location). Instruments used for first stage: city level dummies for all cities with at least one higher education institution (University or College) in the top 100 THE or QS lists for the period 2004–2013 (Source: http://www.universityrankings.ch).
Robust standard errors in parentheses; ***$p < 0.01$, **$p < 0.05$, *$p < 0.1$.

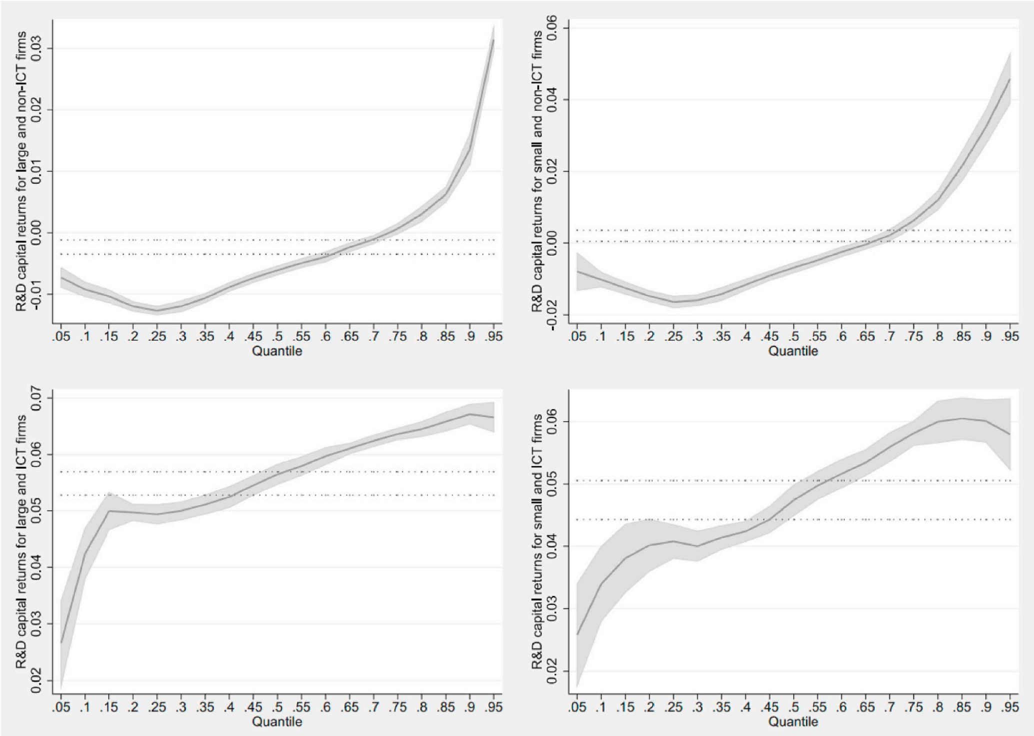

Fig. 2. R&D quantile regression plots for small and large ICT and non-ICT firms.

5.2. *Quantile analysis*

We are also interested in the distribution of these effects across our sample. So far, we have tried to explicitly label firms in terms of age and size but there may still be some uncaptured firm effects that help explain this wide variation across small and old ICT firms and the rest of the sample. For this purpose, we undertake a quantile regression analysis. We follow the approach introduced by Canay (2011) using two stages. The first stage estimates the residuals for the model in Equation (3); in the second stage these are then fitted into a quantile regression model with a new dependent variable which is calculated as the difference from the original minus the estimated residuals (Canay, 2011) and plot the findings for different levels of firm revenues. We visually present these analyses in Figs. 2 and 3. The numeric results are in the Supplementary Materials (Table S4).

Quantile analyses demonstrate that the R&D effect grows consistently for ICT firms as revenues increase (ignoring the ends of the distribution that have few observations). Fig. 2 shows that the R&D effect is stronger throughout for small firms rather than larger firms, supporting our earlier findings (see y-axis in Fig. 2). Fig. 3 shows that the R&D effect is greater for older ICT firms than their younger counterparts, also supporting our earlier findings.

5.3. *Klette (1996) framework*

As a further robustness test, we apply the performance index framework of Klette (1996) that enhances the standard Cobb-Douglas approach (a full description of the method is in the Appendix). Klette's performance index is essentially a Solow residual with the total output replaced by revenue. This index represents a metric of total factor productivity that can accommodate complementarities among knowledge components within firms and the persistence of knowledge capital (Klette, 1996).

We apply this method as the perpetual inventory method has a shortcoming. In particular, uniform depreciation rates tend to simplify the varying effects of R&D across firms, although the choice of a specific rate (either arbitrarily or via a modeling framework) does not seem to affect the resulting elasticities (Fraumeni & Okubo, 2005; Hall, Mairesse, & Mohnen, 2010). This shortcoming may be significant in our study because ICT industries are characterized by quick changes in technology and product design, so that using common firm deflators results in biased estimates in the production functions. The creation of new markets (smartphones, tablets, Internet of Things, apps, etc.) or the substitution of traditional ones (with websites and platforms) creates an environment of imperfect competition with prices for various products reflecting idiosyncratic differences in cost.

Table 6 presents the results of the Klette (1996) framework adding indicators for ICT versus non-ICT firms; small and large firms; and young and old firms. These results support our main findings with a larger positive effect of R&D on the performance index for ICT firms than non-ICT, for small ICT firms, and for old and small ICT firms.

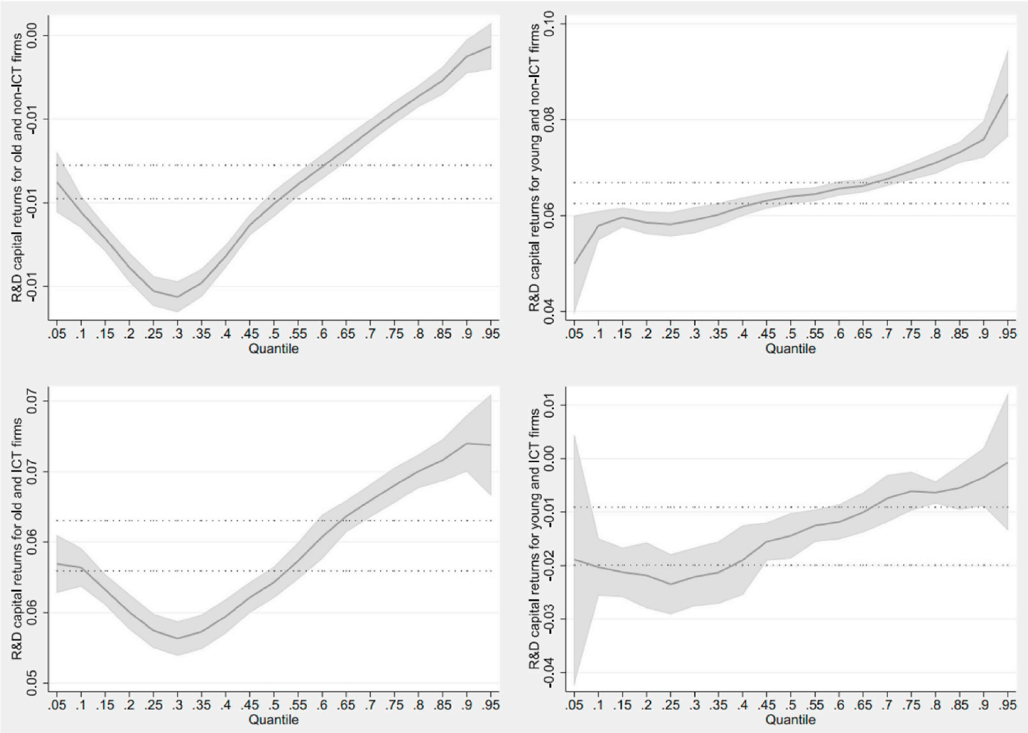

Fig. 3. R&D quantile regression plots for old and young ICT and non-ICT firms.

5.4. Robustness test: value added as dependent variable

Finally, we estimated the models using value added as the dependent variable.[15] These results strongly support our core argument, in that smaller and older ICT firms benefit the most from R&D. However, we note that using value-added also resulted in young ICT firms losing significance in the main model equivalent of Table 2, even though young ICT firms do have an economically and statistically significant coefficient in the equivalent of Table 4. Thus, the separate estimations of the R&D coefficient for large & young and small & young ICT firms do not properly identify either. We speculate this may have to do with the fact that for young ICT firms scaling activities may be severely constrained by resource availability and thus when revenues grow as a result of R&D, value added grows more slowly.

6. Discussion and conclusion

In this paper we examine firms that reported some R&D activity in four European countries over a decade (2004–2013) and compare the effect of R&D resources on their performance. These firms are already different and scarce (less than 1 percent of the total firms in the Orbis dataset) from the majority of others in the market as they try to innovate and appropriate their findings to increase sales and profits. In this setting we distinguish between firms in the ICT domain and the rest. We also look into other firm level characteristics that can moderate this relationship including firm age and size.

Our major finding is that ICT firms are associated with a greater effect of R&D investment on firm revenues and performance that non-ICT firms. ICTs continue to present rich and valuable technological opportunities for firms to grasp and capitalize upon (Klevorick et al., 1995). We argue that this occurs for two reasons: the special characteristics of ICT goods and services and the effect of ICT adoption on ICT firms. ICT is a general-purpose technology that can be (and has been) adopted in many if not all economic sectors. ICT products tend to have applications across multiple industry sectors and hence large markets; for instance, think of the broad demand for such ICT products and services as the basic personal computer, smartphone, email, or search engine. Therefore, R&D investments in ICT product and service development may result in greater revenue growth through the absolute size and expansion of the addressable market, whereas R&D investments into non-ICT products and services may have narrower appeal. Another characteristic of many ICT products and services is that they are associated with network effects that may induce winner-take-all market dynamics, whereby a single ICT product or service dominates the market. Network effects occur when the value of the product or service to customers increases the more it is adopted by other customers. Thus, for those ICT products and services that are

[15] Although the Orbis/Amadeus dataset does not contain a value-added variable, we constructed a measure of value added (revenue minus intermediates). The results are available from the corresponding author upon request.

Table 6
Klette (1996) framework results.

Variables	(1)	(2)	(3)	(4)	(5)	(6)
	GMM	2SLS	Include extra IV	GMM	GMM	GMM
Performance Index (t-1)	0.910***	0.922***	0.915***	0.910***	0.910***	0.909***
	(0.00754)	(0.00767)	(0.00735)	(0.00754)	(0.00764)	(0.00765)
Assets	−0.0679***	−0.0538***	−0.0539***	−0.0679***	−0.0690***	−0.0711***
	(0.00755)	(0.00777)	(0.00775)	(0.00755)	(0.00764)	(0.00779)
Assets (t-1)	0.0645***	0.0499***	0.0496***	0.0645***	0.0682***	0.0695***
	(0.00677)	(0.00709)	(0.00709)	(0.00677)	(0.00672)	(0.00685)
R&D (t-1)	0.0165***	0.0149***	0.0152***			
	(0.00267)	(0.00268)	(0.00267)			
"No R&D" (t-1) dummy	−0.00897***	−0.00836***	−0.00873***	−0.00896***	−0.0143***	−0.0138***
	(0.00252)	(0.00252)	(0.00252)	(0.00253)	(0.00273)	(0.00276)
non-ICT firms R&D (t-1)				0.0164***		
				(0.00274)		
ICT firms R&D (t-1)				0.0173***		
				(0.00328)		
large & non-ICT firms R&D (t-1)					0.0139***	
					(0.00292)	
small & non-ICT firms R&D (t-1)					0.0260***	
					(0.00312)	
large & ICT firms R&D (t-1)					0.0158***	
					(0.00367)	
small & ICT firms R&D (t-1)					0.0274***	
					(0.00451)	
old & large & non-ICT firms R&D (t-1)						0.0155***
						(0.00288)
young & large & non-ICT firms R&D (t-1)						0.00388
						(0.00683)
old & small & non-ICT firms R&D (t-1)						0.0254***
						(0.00325)
young & small & non-ICT firms R&D (t-1)						0.0256***
						(0.00333)
old & large & ICT firms R&D (t-1)						0.0174***
						(0.00377)
young & large & ICT firms R&D (t-1)						0.000431
						(0.0137)
old & small & ICT firms R&D (t-1)						0.0295***
						(0.00476)
young & small & ICT firms R&D (t-1)						0.0140
						(0.00967)
Constant	−0.00812**	−0.00626	−0.00619	−0.00815**	−0.00851**	−0.00847**
	(0.00411)	(0.00412)	(0.00411)	(0.00411)	(0.00413)	(0.00412)
Firm FE	Yes	Yes	Yes	Yes	Yes	Yes
Year X NACE FE	Yes	Yes	Yes	Yes	Yes	Yes
Year X Country FE	Yes	Yes	Yes	Yes	Yes	Yes
Hansen J-stat	68.231	68.231	80.612	68.243	81.96	80.655
Observations	42,811	42,811	42,811	42,811	42,811	42,811
R-squared	0.698	0.696	0.697	0.698	0.698	0.699

Robust standard errors in parentheses; ***$p < 0.01$, **$p < 0.05$, *$p < 0.1$.

associated with network effects, such as most communication services, investments in R&D can have an outsized impact on revenue as compared to non-networked (and non-ICT) products.

Our second contribution is that smaller firms, in general, enjoy a greater impact of R&D on revenue performance. Although this effect is most pronounced for ICT firms, it is also present for non-ICT firms. Smaller size may confer greater flexibility and adaptability of R&D and managerial processes, enabling exploitation of technological and market shifts. For instance, Rothwell and Dodgson (1994) suggest that smaller organizations enjoy organizational and behavioral advantages, benefiting from more rapid decision-making. Furthermore, smaller firms may allow their R&D personnel to be more creative which the conservatism of larger hierarchical structures limit (Acs & Audretsch, 1990). Moreover the size of a firm tends to characterize its position in the market. For example, larger firms may prefer to acquire smaller rivals that tend to be innovative instead of developing the research in-house. This has a dual effect on their performance: it reduces the risk of a new research endeavor and, at the same time, reduces the threat of entry from a competitor. Other potential explanations could be factors which require smaller firms to be more efficient in their use of R&D investment, such as financial restrictions, size-dependent regulation, or the presence of state-owned enterprises.[16]

[16] We thank an anonymous reviewer for pointing this out.

Our counter-intuitive third finding is that older ICT firms demonstrate a greater R&D effect on revenue performance relative to younger firms. While young firms are generally assumed to be more innovative because they are not bound by existing structures or traditions (Majumdar, 1997), with age firms can accumulate reputations and beneficial market positions which facilitate relationships with suppliers, customers and potential collaborators, leading to improved performance. Extant scholarship has found that older firms are advantaged in terms of their managerial knowledge and ability to handle uncertainty (Herriott et al., 1985; Levitt & March 1988).

A cursory overview of the subsample of small and old ICT firms in our dataset suggests that these firms typically dominate specific market niches. Examples include firms that provide specialist ICT for the biotechnology, specialist ICT for the media industry, and specialist electro-mechanical hardware for the automotive and manufacturing industries.[17] Hence we suggest that the agility and flexibility afforded by a small firm size are complemented by accumulated capabilities, experience and market access. Older firms that dominate market niches accumulate a reputation and develop productive and powerful relationships with suppliers, customers and potential collaborators, leading to greater R&D effectiveness.[18]

For managers of larger, older ICT firms, our results suggest adopting organizational arrangements that mimic the small-firm environment. Examples of such arrangements include the original development of the IBM microcomputer in a separate and independent unit in Boca Raton, Florida, and, more recently, development of the Watson business unit located in Manhattan, instead of Armonk in upstate New York where most of IBM innovation has taken place. A small and independent unit allows faster adaptation to technological and market opportunities. For young and small ICT firms, these results suggest that the greatest R&D impact may come from identifying a market niche and dominating it, as classically suggested by Porter (1985). More research is needed, however, to identify what underlying characteristics of older niche firms allow them to be more effective innovators—e.g., whether it is the accumulated industry experience or operational capabilities, existing supplier and complementor relationships, or the customer base that is the primary underlying factor.

These results also suggest that policy makers concerned with innovation-driven growth should target R&D incentives at ICT firms. Our findings underline the impressive contribution that small research budgets can have in this technology sector (OECD, 2015). Research to date has demonstrated that R&D incentives are more effective for smaller firms than for larger ones. For instance, Bronzini and Piselli (2016) find that the smaller the firm, the greater the impact of an R&D policy on the intensity and probability of patenting. Similarly, Criscuolo et al. (2012) find that R&D incentive programs have a positive effect on employment, investment and net entry (but not total factor productivity) for smaller firms.

Current European policy has been focusing on ICT incentives with such programs as the European Institute of Innovation and Technology EIT Digital, which is charged to deliver digital innovation and digital entrepreneurial education. However, much of the current policy interest is based upon the observation that Europe has fewer startup innovators than the US, in relative terms. Scholars suggest European policy makers should seek to address this (Veugelers & Cincera, 2010). Similarly, many national R&D policies focus on younger firms. Our results suggest that, in the ICT sector at least, policies should not exclude older firms.

One potential R&D policy would be a R&D Tax Relief Scheme. Recent research into the UK R&D Tax Relief Scheme had a large innovation output impact for smaller firms. In particular, Dechezleprêtre, Einiö, Martin, Nguyen, and Van Reenen (2016) found that R&D approximately doubled and patenting rose by about 60% after the intervention of tax relief, and that this effect was particularly strong for smaller firms who are more responsive to R&D tax credits. Their simple calculations suggest that between 2006 and 2011 the UK R&D Tax Relief Scheme induces £1.7 of private R&D for every £1 of taxpayer money and that aggregate UK business R&D would have been about 10% lower in the absence of the policy.

Policy interventions for older firms are less common. In the US, the Small Business Administration and its SBIR and STTR grant programs do not have formal age criteria for funding, only requiring fewer than 500 employees and private ownership.[19] However, such grant funding is restricted to firms before major external capitalization, and only can be sought when venture capital operating companies, hedge funds, private equity firms, or any combination of these, control less than 50% of the equity. Similarly, in the UK there is no formal age criteria. To quality for R&D tax relief, a small or medium-sized enterprise must have fewer than 500 employees with either an annual turnover under €100 million or a balance sheet under €86 million.[20]

Both these examples suggest that existing R&D policy interventions may have the effect of implicitly preferring younger firms, although they would not preclude all older firms. We recommend relaxing any conditions for R&D funding related to firm age, beginning with a review of existing R&D policy interventions to increase access to R&D funding for smaller yet older firms. Particularly in ICT, the optimal firm size for innovation may be small, and firms should not be penalized for staying small. Put differently, policies should not focus only on startups but on experienced firms too, so long as they are small and innovative.

[17] A full list is available from the corresponding author upon request.

[18] We also observed that some of these smaller and older firms were part of larger business groups (a common phenomenon in Europe) that might facilitate access to group level R&D. To determine whether the R&D impact was influenced by membership in a business group, we reran the regressions with an interaction effect for group membership. We found that small, old and ICT firms that do *not* belong to groups have a higher R&D effect on revenues, suggesting that the overall result is not driven by access to group-level R&D.

[19] US Small Business Administration; https://sbir.nih.gov; retrieved 10/02/2017.

[20] UK HMRC; https://www.gov.uk/guidance/corporation-tax-research-and-development-tax-relief-for-small-and-medium-sized-enterprises; retrieved 10/02/2017.

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Appendix A. Supplementary data

Supplementary data to this article can be found online at https://doi.org/10.1016/j.telpol.2019.101833.

References

Acemoglu, D., & Zilibotti, F. (2001). Productivity differences. *Quarterly Journal of Economics, 116*(2), 563–606.
Acs, Z. J., & Audretsch, D. B. (1988). Innovation in large and small firms: An empirical analysis. *The American Economic Review, 78*(4), 678–690.
Acs, Z. J., & Audretsch, D. B. (1990). *Innovaton and small firms.* Cambridge, MA: MIT Press.
Adalet McGowan, M., Andrews, D., & Millot, V. (2018). The walking dead? Zombie firms and productivity performance in oecd countries. *Economic Policy, 33*(96), 685–736.
Adams, J. D., & Jaffe, A. B. (1996). Bounding the effects of r&d: An investigation using matched establishment-firm data. *The RAND Journal of Economics, 27*(4), 700–721.
Andrews, D., & Cingano, F. (2014). Public policy and resource allocation: Evidence from firms in oecd countries. *Economic Policy, 29*(78), 253–296.
Andrews, D., Criscuolo, C., & Gal, P. N. (2015). *Frontier firms, technology diffusion and public policy: Micro evidence from oecd coutnries, the Future of Productivity: Main Background Papers.* Paris, France: OECD.
Angrist, J. D. (2004). Treatment effect heterogeneity in theory and practice. *The Economic Journal, 114*(494), C52–C83.
Arellano, M., & Bover, O. (1995). Another look at the instrumental variable estimation of error-components models. *Journal of Econometrics, 68*(1), 29–51.
Azoulay, P., Jones, B., Kim, J. D., & Miranda, J. (2018). *Age and high-growth entrepreneurship.* National Bureau of Economic Research Working Paper Series No. 24489.
Balasubramanian, N., & Lee, J. (2008). Firm age and innovation. *Industrial and Corporate Change, 17*(5), 1019–1047.
Baqaee, D. R., & Farhi, E. (2017). *The macroeconomic impact of microeconomic shocks: Beyond hulten's theorem.* National Bureau of Economic Research Working Paper Series No. 23145.
Bardhan, I., Krishnan, V., & Lin, S. (2013). Research note—business value of information technology: Testing the interaction effect of it and r&d on tobin's q. *Information Systems Research, 24*(4), 1147–1161.
Beck, N., & Katz, J. N. (1997). *The analysis of binary time-series-cross-section data and/or the democratic peace.* Columbus, OH: Annual Meeting of the Political Methodology Group.
Bloom, N., Sadun, R., & Ven Reenen, J. (2012). Americans do it better: Us multinationals and the productivity miracle. *The American Economic Review, 102*(1), 167–201.
Blundell, R., & Bond, S. (1998). Initial conditions and moment restrictions in dynamic panel data models. *Journal of Econometrics, 87*(1), 115–143.
Bresnahan, T. F. (1986). Measuring the spillovers from technical advance: mainframe computers in financial services. *The American Economic Review,* 742–755.
Bresnahan, T. F., & Trajtenberg, M. (1995). General purpose technologies 'engines of growth'? *Journal of Econometrics, 65*(1), 83–108.
Bronzini, R., & Piselli, P. (2016). The impact of r&d subsidies on firm innovation. *Research Policy, 45*(2), 442–457.
Brynjolfsson, E., & Hitt, L. M. (2003). Computing productivity: Firm-level evidence. *The Review of Economics and Statistics, 85*(4), 793–808.
Brynjolfsson, E., Rock, D., & Syverson, C. (2018). Artificial intelligence and the modern productivity paradox: A clash of expectations and statistics. In A. K. Agrawal, J. S. Gans, & A. Goldfarb (Eds.). *The economics of artificial intelligence: An agenda*. Chicago, IL: University of Chicago Press.
Calligaris, S., Del Gatto, M., Hassan, F., Ottaviano, G. I. P., & Schivardi, F. (2018). The productivity puzzle and misallocation: An Italian perspective. *Economic Policy, 33*(96), 635–684.
Canay, I. A. (2011). A simple approach to quantile regression for panel data. *The Econometrics Journal, 14*(3), 368–386.
Coad, A., & Rao, R. (2008). Innovation and firm growth in high-tech sectors: A quantile regression approach. *Research Policy, 37*(4), 633–648.
Coad, A., Segarra, A., & Teruel, M. (2016). Innovation and firm growth: Does firm age play a role? *Research Policy, 45*(2), 387–400.
Cohen, W. M. (1995). Empirical studies of innovative activity. In P. Stoneman (Ed.). *Handbook of the economics of innovation and technological change: 182-264*. Oxford, UK: Blackwell.
Cohen, W. M., & Klepper, S. (1996). A reprise of size and r & d. *The Economic Journal, 106*(437), 925–951.
Cohen, W. M., & Levinthal, D. A. (1989). Innovation and learning: The two faces of r & d. *The Economic Journal, 99*, 569–596.
Criscuolo, C., Martin, R., Overman, H., & Van Reenen, J. (2012). *The causal effects of an industrial policy.* NBR Working Papers.
Czarnitzki, D., & Hottenrott, H. (2011). R&d investment and financing constraints of small and medium-sized firms. *Small Business Economics, 36*(1), 65–83.
Daveri, F., & Maliranta, M. (2007). Age, seniority and labour costs: Lessons from the Finnish it revolution. *Economic Policy, 22*(49), 117–175.
Dechezleprêtre, A., Einiö, E., Martin, R., Nguyen, K.-T., & Van Reenen, J. (2016). *Do tax incentives for research increase firm innovation? An rd design for r&d. NBER working paper series.* National Bureau of Economic Research.
Decker, R. A., Haltiwanger, J., Jarmin, R. S., & Miranda, J. (2015). *Where has all the skewness gone? The decline in high-growth (young) firms in the us.* NBER Working Paper Series.
Del Monte, A., & Papagni, E. (2003). R&d and the growth of firms: Empirical analysis of a panel of Italian firms. *Research Policy, 32*(6), 1003–1014.
Dosi, G. (1982). Technological paradigms and technological trajectories. *Research Policy, 11*(3), 147–162.
Ezell, S., & Andes, S. (2010). Ict r&d policies: An international perspective. *IEEE Internet Computing, 14*(4), 76–88.
Fraumeni, B. M., & Okubo, S. (2005). R&d in the national income and product accounts: A first look at its effect on gnp. In C. Corrado, J. Haltiwanger, & D. E. Sichel (Eds.). *Measuring capital in the new economy*. Chicago, IL: University of Chicago Press.
García-Quevedo, J., Pellegrino, G., & Vivarelli, M. (2014). R&d drivers and age: Are young firms different? *Research Policy, 43*(9), 1544–1556.
Geroski, P. A., & Machin, S. (1992). Do innovating firms outperform non-innovators? *Business Strategy Review, 3*(2), 79–90.
Goldin, I., Koutroumpis, P., Lafond, F., Rochowicz, N., & Winkler, J. (2018). *Why is productivity slowing down? Working paper.* Oxford Martin School: University of Oxford.
Gordon, R. J. (2000). Does the "new economy" measure up to the great inventions of the past? *The Journal of Economic Perspectives, 14*(4), 49–74.
Griffith, R., Harrison, R., & Van Reenen, J. (2006). How special is the special relationship? Using the impact of us r&d spillovers on UK firms as a test of technology sourcing. *The American Economic Review, 96*(5), 1859–1875.
Griliches, Z. (1990). Patents as economic indicators: A survey. *Journal of Economic Literature, 28*(4), 1661–1707.
Griliches, Z. (1998). *R&d and productivity: The econometric evidence.* Chicago, IL: The University of Chicago Press.
Griliches, Z. (2007). *R&d, patents and productivity.* Chicago, IL: University of Chicago Press.
Hall, B. H., Lotti, F., & Mairesse, J. (2013). Evidence on the impact of r&d and ict investments on innovation and productivity in Italian firms. *Economics of Innovation and New Technology, 22*(3), 300–328.
Hall, B. H., & Mairesse, J. (1995). Exploring the relationship between r&d and productivity in French manufacturing firms. *Journal of Econometrics, 65*(1), 263–293.
Hall, B. H., Mairesse, J., & Mohnen, P. (2010). Measuring the returns to r&d. In B. H. Hall, & N. Rosenberg (Vol. Eds.), *Handbook of the economics of innovation: Vol. 2*, (pp. 1033–1082). Amsterdam, NL: Elsevier BV Vol. 2.
Hall, B. H., & Oriani, R. (2006). Does the market value r&d investment by european firms? Evidence from a panel of manufacturing firms in France, Germany, and

Italy. *International Journal of Industrial Organization, 24*(5), 971–993.
Hausman, J. A., Hall, B. H., & Griliches, Z. (1984). Econometric models for count data with an application to the patents-r&d relationship. *Econometrica, 52*(4), 909–938.
Herriott, S. R., Levinthal, D., & March, J. G. (1985). Learning from experience in organizations. *The American Economic Review, 75*(2), 298–302.
Hitt, L. M., & Brynjolfsson, E. (1996). Productivity, business profitability, and consumer surplus: Three different measures of information technology value. *MIS Quarterly, 20*(2), 121–142.
Huergo, E., & Jaumandreu, J. (2004). How does probability of innovation change with firm age? *Small Business Economics, 22*(3/4), 193–207.
Keele, L., & Kelly, N. J. (2006). Dynamic models for dynamic theories: The ins and outs of lagged dependent variables. *Political Analysis, 14*(02), 186–205.
Keller, W. (1998). Are international R&D spillovers trade-related?: Analyzing spillovers among randomly matched trade partners. *European Economic Review, 42*(8), 1469–1481.
Kleis, L., Chwelos, P., Ramirez, R. V., & Cockburn, I. (2012). Information technology and intangible output: The impact of it investment on innovation productivity. *Information Systems Research, 23*(1), 42–59.
Klette, T. J. (1996). R&d, scope economies, and plant performance. *The RAND Journal of Economics, 27*(3), 502–522.
Klevorick, A. K., Levin, R. C., Nelson, R. R., & Winter, S. G. (1995). On the sources and significance of interindustry differences in technological opportunities. *Research Policy, 24*(2), 185–205.
Koutroumpis, P., Leiponen, A., & Thomas, L. D. W. (2017a). How important is "it"? *Communications of the ACM, 60*(7), 62–68.
Koutroumpis, P., Leiponen, A., & Thomas, L. D. W. (2017b). Invention machines: How instruments and information technologies drive global technological progress. *ETLA working papers, ETLA - the research Institute of the Finnish economy*http://pub.etla.fi/ETLA-Working-Papers-52.pdf.
Levitt, B., & March, J. G. (1988). Organizational learning. *Annual Review of Sociology, 14*(1), 319–338.
Mairesse, J., & Mohnen, P. (2004). The importance of r&d for innovation: A reassessment using French survey data. *The Journal of Technology Transfer, 30*(1–2), 183–197.
Majumdar, S. K. (1997). The impact of size and age on firm-level performance: Some evidence from India. *Review of Industrial Organization, 12*(2), 231–241.
Mansfield, E. (1980). Basic research and productivity increase in manufacturing. *The American Economic Review, 70*(5), 863–873.
Mishra, A. N., & Agarwal, R. (2010). Technological frames, organizational capabilities and it use: An empirical investigation of electronic procurement. *Information Systems Research, 21*(2), 249–270.
OECD (2013). *Oecd science, technology and industry scoreboard 2013.* Paris, France: Organisation for Economic Co-operation and Development.
OECD (2015). *Oecd science, technology and industry scoreboard 2015.* Paris, France: Organisation for Economic Co-operation and Development.
Pakes, A., & Schankerman, M. (1984). *The rate of obsolescence of patents, research gestation lags, and the private rate of return to research resources,* ***R&d, patents, and productivity***. University of Chicago Press73–88.
Peters, B., Roberts, M. J., Vuong, V. A., & Fryges, H. (2017). Estimating dynamic r&d choice: An analysis of costs and long-run benefits. *The RAND Journal of Economics, 48*(2), 409–437.
Porter, M. E. (1985). *Competitive advantage: Creating and sustaining superior performance.* New York, NY: Free Press.
Revilla, A. J., & Fernández, Z. (2012). The relation between firm size and r&d productivity in different technological regimes. *Technovation, 32*(11), 609–623.
Romer, P. M. (1994). The origins of endogenous growth. *The Journal of Economic Perspectives, 8*(1), 3–22.
Rothwell, R., & Dodgson, M. (1994). Innovation and size of firm. In M. Dodgson, & R. Rothwell (Eds.). *The handbook of industrial innovation: 310-324*. Aldershot, UK: Edward Elgar.
Scherer, F. M. (1965). Firm size, market structure, opportunity, and the output of patent innovations. *The American Economic Review, 55*(5), 1097–1125.
Sorensen, J. B., & Stuart, T. E. (2000). Aging, obsolescence, and organizational innovation. *Administrative Science Quarterly, 45*(1), 81–112.
Srinivasan, R., Lilien, G. L., & Rangaswamy, A. (2002). Technological opportunism and radical technology adoption: An application to e-business. *Journal of Marketing, 66*(3), 47–60.
Tambe, P., & Hitt, L. M. (2014). Measuring information technology spillovers. *Information Systems Research, 25*(1), 53–71.
Veugelers, R., & Cincera, M. (2010). *Europe's missing yollies.* Brussels, Belgium: Bruegal Policy Brief.