Research Policy 45 (2016) 387–400

Contents lists available at ScienceDirect

Research Policy

journal homepage: www.elsevier.com/locate/respol

Innovation and firm growth: Does firm age play a role?

Alex Coad[a,b,*], Agustí Segarra[c], Mercedes Teruel[c]

[a] European Commission, Joint Research Centre (JRC), Institute for Prospective Technological Studies (IPTS), Knowledge for Growth Unit, Edificio Expo. C/ Inca Garcilaso 3, 41092 Seville, Spain
[b] Science Policy Research Unit (SPRU), Jubilee Building, University of Sussex, Falmer, Brighton BN19SL, UK
[c] Universitat Rovira i Virgili, Grup de Recerca d'Indústria i Territori, XREAP, Avda. Universitat 1, 43204 Reus, Spain

ARTICLE INFO

Article history:
Received 22 July 2014
Received in revised form 23 October 2015
Accepted 24 October 2015
Available online 21 November 2015

JEL classification:
L25
L20

Keywords:
Firm age
Firm growth
Innovation
Panel quantile regression
Scale-up
Post-entry growth

ABSTRACT

This paper explores the relationship between innovation and firm growth for firms of different ages. We hypothesize that young firms undertake riskier innovation activities which may have greater performance benefits (if successful), or greater losses (if unsuccessful). Using an extensive Spanish Community Innovation Survey sample for the period 2004–2012, we apply panel quantile regressions to study the effect of R&D activities on firm growth (i.e. sales growth, productivity growth and employment growth). Our results show that young firms face larger performance benefits from R&D at the upper quantiles of the growth rate distribution, but face larger decline at the lower quantiles. R&D investment by young firms therefore appears to significantly riskier than R&D investment by more mature firms, which suggests some policy implications.

1. Introduction

In recent years there has been growing attention to the phenomenon of young innovative companies (Schneider and Veugelers, 2010; Czarnitzki and Delanote, 2013; Audretsch et al., 2014). Indeed, the fast-growing, job-creating innovative entrepreneur has so much appeal because of the close resemblance to the Schumpeterian ideal-type (Coad and Reid, 2012; Daunfeldt et al., 2015). Considerable policy interest surrounds the observation that Europe has fewer young large leading innovators (or 'yollies') than the US, and it has been suggested that European policy-makers should seek to increase the number of young large leading innovators (Veugelers and Cincera, 2010). Relatedly, a number of contributions in the Industrial Organization literature have emphasized that it is young firms (rather than small firms) that make the largest contribution to job creation (Haltiwanger et al., 2013; Lawless, 2014; Hyytinen and Maliranta, 2013). One of the major difficulties faced by young European firms appears to be the existence of barriers to post-entry growth (Bartelsman et al., 2005). In this paper, we contribute to the literature by focusing on how R&D investment affects growth in young firms.

The previous empirical literature has taken a variety of approaches to investigate how the nature of innovation changes with firm age. Theory and evidence have shown that entrants invest more in R&D than incumbents when the task is to enter new markets (Reinganum, 1983; Czarnitzki and Kraft, 2004), which suggests that old firms may be less R&D-intensive than their younger counterparts. Some scholars have even suggested that the innovative contribution of new firms is so valuable that industrial policy should subsidize entrants at the same time as taxing incumbents (Acemoglu et al., 2013). Other scholars have investigated the relationship between firm age and probability of innovation, paying attention to the distinction between product and process innovation (Huergo and Jaumandreu, 2004a,b; Cucculelli, 2014). Others have presented evidence that the effects of age on innovation are affected by learning (as firms gain experience and build on previous routines and capabilities) and obsolescence (as the directions of search are outdated and are not well-suited to the current technological landscape) (Sorensen and Stuart, 2000; see also

* Corresponding author at: JRC-IPTS, European Commission, Knowledge for Growth (KFG), Edificio EXPO, ITPS, C/ Inca Garcilaso, 3 E-41092 Seville, 41092 Sevilla, Spain. Tel.: +44 954487185.
E-mail addresses: Alexander.Coad@ec.europa.eu, alex.coad@gmail.com (A. Coad).

http://dx.doi.org/10.1016/j.respol.2015.10.015
0048-7333/

Criscuolo et al., 2012). Balasubramanian and Lee (2008) observe that firm age is negatively related to technical quality, and that the effect is greater in technologically active areas. Firm age also plays a role on the likelihood of superior organizational outcomes (Argote, 1999), new product development (Hansen, 1999; Sivadas and Dwyer, 2000), investment in R&D (García-Quevedo et al., 2014), innovative outcomes (Tripsas and Gavetti, 2000), and other areas of firm strategy (BarNir et al., 2003). We complement the literature by investigating the moderating role of age on the relationship between R&D investment and firm growth.

Although previous empirical investigations of firm-level innovation have lacked detailed data on firm age (Headd and Kirchhoff, 2009; Decker et al., 2014), we analyze a rich new dataset to gain a number of novel insights into the influence of age on innovation, as well as the effects of innovation on firm growth (conditional on age). Our measure of innovative activity is R&D expenditure per employee. We distinguish between young firms (less than 10 years old) and other, older firms. We develop several hypotheses that acknowledge that firms' innovation processes change over a firm's life course, building on notions that as firms get older, they gain experience and become more routinized. We analyze panel data on Spanish innovative firms between 2004 and 2012. The data source is the Technological Innovation Panel (PITEC—Panel de Innovación Tecnológica) which compiles the Spanish surveys of the Community Innovation Survey (CIS). Our regressions focus on three alternative indicators of firm growth: growth of sales, growth of productivity and growth of employment. Panel quantile regressions reveal that youth amplifies the riskiness of innovative activities—young innovative firms may either enjoy large upside gains or large downside losses. Our results suggest that young firms are particularly vulnerable to the risks inherent in innovative activity.

The structure of the paper is as follows. Section 2 outlines the literature related to firm age and innovation. Section 3 presents our hypotheses on the effect of R&D investment on growth as firms age. Section 4 presents the database and some descriptive statistics. Section 5 shows the econometric methodology and variables. Section 6 reports the results of the effect of firm age and innovation on firm performance, and Section 7 concludes.

2. Innovation, firm growth, and the moderating effect of firm age: A literature review

While some studies have focused on how innovation changes with age, other studies – more closely related to our present paper – focus on how age moderates the ways in which firms benefit from innovation. In fact, the empirical literature has found both negative and positive influences of firm age.

Older firms may enjoy advantages stemming from their innovation investments. Research has highlighted the existence of learning effects, which allow mature firms to innovate more effectively as they build on previous routines and capabilities. As time goes by, firms innovate on the basis of existing capabilities and competences, and work to refine older areas of technological opportunity. Furthermore, as time goes by, firms are able to accumulate resources, managerial knowledge and the ability to handle uncertainty (Herriott et al., 1984; Levitt and March, 1988), as well as accumulating reputation and market position, which together help facilitate relationships and contacts with customers, suppliers and potential collaborators. Finally, there is evidence on the positive effect of firm age on the likelihood of superior organizational outcomes (Argote, 1999), new product development (Hansen, 1999; Sivadas and Dwyer, 2000) and innovative outcomes (Tripsas and Gavetti, 2000).

However, older firms may suffer from a number of drawbacks that hinder their ability to translate R&D investment into higher growth rates. It has been pointed out that organizational inertia may constrain the firm's ability to change. For instance, Majumdar (1997) noted that older firms are liable to experience some form of inertia, which may hinder learning effects. Furthermore, firm experience may generate obsolescence if the directions of search activities upon which mature firms have embarked are not well suited to the contemporaneous technological landscape. Relatedly, Sorensen and Stuart (2000) identify two effects of age on innovation – learning effects and obsolescence effects – and they present evidence supporting both of these contrasting effects in their analysis of semiconductor and biotechnology firms. Balasubramanian and Lee (2008) analyze data on patents of Compustat firms in order to examine how firm age relates to innovation quality, and how this link varies depending on the nature of technology. They found that firm age is negatively related to technical quality, and that this effect is greater in technologically active areas.

Regarding younger firms, there may also be opposed effects. On the one hand, young firms start with neither routines nor capabilities, and must establish these rapidly upon entry (Helfat and Peteraf, 2003). The challenge is for young firms, starting from scratch, to quickly set up not only everyday operating routines but also higher-level innovation capabilities. Young firms may therefore initially lack the internal capabilities to benefit from R&D investment. The classic distinction between local search and distant (exploratory) search (Katila and Ahuja, 2002) is less clear in the context of young firms, because they do not yet have an established stock of production knowledge or innovative routines that would allow them to engage in local search. What is routine and 'local' for established firms may still require lots of planning on the part of new firms—"New firms are hampered by their need to make search processes a prelude to every new problem they encounter" (Garnsey, 1998, p541). On the other hand, these firms may acquire external knowledge by investing in external R&D. In this vein, Pellegrino et al. (2012) investigate the difference between young innovative companies (YICs) and their older counterparts using Italian CIS data. Those authors observe that embodied technical change (that is, investments in innovative machinery and equipment) plays an especially large role for YICs, although there is a conspicuous lack of an effect of internal R&D on innovation intensity in the case of YICs. Taken together, this might indicate that YICs have difficulties in accumulating internal R&D capabilities in the years following start-up, and source other types of innovation inputs.

Consequently, previous empirical evidence indicates that new firms typically need time to accommodate to the situation within which they operate and improve their internal capabilities. They also have to assess how their performance relates to the performance of their competitors and in which ways performance needs to be improved. As Taymaz (2005, p. 430) puts it: "new firms become aware of their actual productivity after observing their performance in the industry". In fact, this is consistent with the finding that new firms generally enter with productivity levels lower than that of incumbents (Jensen et al., 2001; Huergo and Jaumandreu, 2004a,b; Coad et al., 2013). When the performance of new firms is below that of the existing firms in the market, new firms need to catch up in order to be competitive.

The small but growing literature on how innovative activity changes with firm age has therefore developed along a number of different avenues. We contribute to the literature by presenting new evidence on the moderating role of age on the relationship between R&D investment and firm growth, when growth is measured in terms of sales, productivity, or employment. In particular, we apply panel quantile regression to investigate how the effect of innovation on growth varies across the growth rate distribution.

While some previous work has applied (cross-sectional) quantile regression estimators to investigate the effect of innovation on sales growth (e.g. Coad and Rao, 2008) or the effect of young innovative companies on sales and employment growth (e.g. Czarnitzki and Delanote, 2013), we present novel evidence on how the relationship between innovation and growth varies between young and old firms. We therefore shed new light on how the nature of innovative activity and performance changes with firm age. Our results show that the R&D investments of young firms are more likely to result in both faster growth rates – and also faster decline – than the R&D investments of older firms.

3. Hypotheses

In this section we derive some hypotheses related to the effect of R&D investments on firm growth, and the role of firm age. We begin by suggesting that R&D expenditure (which is an innovation input) will result in superior performance, because firms' attempts at innovation may lead to innovation outputs that result in increases in market share via the introduction of new products or processes, and to increases in productivity through technical progress. Although investment in R&D is clouded by uncertainty (e.g. uncertainty regarding the returns to innovation and the payback time, uncertainty regarding commercial success of the new products/services, uncertainty regarding appropriability and the threat of imitation by rivals), nevertheless, despite these potential drawbacks, we hypothesize that investments in R&D will be associated with superior performance on average.

Our outcome variable is the growth rates of firms. Firm growth is a multifaceted phenomenon, with indicators such as growth of employment, sales, and productivity shedding light on different aspects of the growth process (Coad, 2010a; Miller et al., 2013). Taking these three alternative growth indicators will therefore provide a richer and more nuanced understanding of how R&D affects the growth of young and old firms. The context of firm-level innovation, in particular, highlights the different issues relating to the influence of R&D investment on these three growth rate indicators. Regarding sales growth: R&D expenditure may lead to sales growth due to additional revenue from new products, but there is also the risk that new innovative products may 'cannibalize' the market share of existing products (Reinganum, 1983; Dachs and Peters, 2014). Productivity growth can be expected to increase after R&D investment, but only if the innovative inputs are successfully translated into innovative outputs (Crepon et al., 1998), that then result in productivity growth (perhaps due to technical progress or the successful introduction of labour-saving process innovations). In other cases, however, productivity growth may also (temporarily) decrease if there are adjustment costs relating to investment in new capacity and the introduction of new production processes, or if there are long time lags between innovation expenditures and subsequent productivity growth. Employment growth may increase after R&D investment, if innovation results in higher demand and higher market share, but it may also decrease if innovation results in labour-saving productivity improvements (Vivarelli et al., 1996; Harrison et al., 2014). These three firm growth indicators shed light on different aspects of how R&D investment may affect firm growth, and we will revisit these distinct facets of our three growth indicators in our subsequent discussion, but for now we hypothesize that R&D investment will have positive effects, overall, on each of the three firm growth indicators.

Hypothesis 1. R&D is positively associated with growth of employees, sales, and productivity, on average.

New firms differ from older firms because, when they enter the market, their stocks of firm-specific knowledge and team-level job tenure experience are fixed at zero. New firms, devoid of routines, must quickly design and implement routines; they must quickly develop capabilities from scratch; and they must rapidly accumulate valuable tacit knowledge. Young firms are unfamiliar with their business environments and, to begin with, face uncertainty regarding all aspects of their business activity (Garnsey, 1998)—and *a fortiori* they face strong uncertainty regarding their innovative activity. Indeed, innovation capabilities may correspond to higher-order capabilities (Winter, 2003) that are particularly complex and difficult to establish, because their development depends on a firm's lower-level routines and capabilities.

The uncertainty surrounding R&D investment by new firms can be a double-edged sword. New firms may benefit from 'a fresh perspective' on the state of the industry and be able to spot new market opportunities or technological opportunities, without being hindered by liabilities of inertia and obsolescence (Barron et al., 1994), and without facing the risk of cannibalizing their established customer base. On the other hand, they may have the flexibility required to capitalize on radical innovation ideas, whereas older firms are more constrained by their existing resources and customer base, and engage in more incremental innovation (Segarra and Teruel, 2014). However, innovative new firms face strong liabilities of newness and inexperience. Older firms may benefit from higher legitimacy, and they may have learned from their past mistakes and thus accumulated valuable experience.

For young firms, therefore, R&D may either have large positive returns (if successful) or large negative returns (if unsuccessful). For old firms, who are more established and routinized, R&D is not purely exploratory but more incremental and developmental (Akcigit and Kerr, 2010). Old firms may thus avoid the risks of radical innovations (which may cannibalize on their existing market share), and they may instead try to better exploit their existing routines and capabilities. Older firms may also be able to apply their experience to identify which R&D projects are more likely to fail, and to terminate them earlier, lowering the overall uncertainty surrounding R&D investments. Furthermore, older firms may have a more diversified portfolio of R&D projects, which would reduce the overall uncertainty of their combined innovation activities.

These differences in the uncertainty surrounding R&D for young and old firms can be related to the distribution of performance outcomes following R&D investment. More specifically, young firms whose innovation activity is riskier may experience higher returns at the upper quantiles of the performance distribution (i.e. higher upside gains) whilst facing the risk of larger losses if innovation attempts are unsuccessful (i.e. larger downside losses). For old firms, the outcome of R&D is expected to be more predictable, and these mature firms will have more moderate positive returns across the distribution. We therefore hypothesize:

Hypothesis 1a. for young firms, R&D investment has a larger positive effect on growth at the upper quantiles of the growth distribution (measured in terms of growth of employment, sales and productivity)

Hypothesis 1b. for young firms, R&D investment has a more negative effect on growth at the lower quantiles of the growth distribution (measured in terms of growth of employment, sales and productivity)

4. Database

Our data source is the Technological Innovation Panel (PITEC - Panel de Innovación Tecnológica) between 2004 and 2012. PITEC contains detailed information from Spanish CIS data related to the innovation behaviour. Our database includes Spanish manufacturing and service firms. Furthermore, the data provides the possibility to study innovation behaviour in a dynamic way, since it tracks yearly the behaviour of firms once they enter the panel. It is manda-

Table 1
Descriptive statistics for the main variables (2006).

Mean values	R&D firms	Non-R&D firms	R&D firms	Non-R&D firms	R&D firms	Non-R&D firms	R&D firms	Non-R&D firms
	Observations		Sales		Productivity		Employees	
<10 years	900	321	28.1	29.0	188,727.2	195,029.0	96.7	128.9
10 to 19 years	1010	499	51.4	22.7	216,828.6	176,407.3	152.6	145.7
20 to 29 years	721	307	26.1	25.2	235,135.1	184,761.2	110.5	147.5
30 or more	1031	411	149.0	78.8	302,429.9	282,811.3	445.7	275.7
Diff. means: Wilks' lambda (Prob > F)			0.9867 (0.000)		0.9960 (0.0001)		0.9791 (0.000)	
	Firm age		GrSales		GrProd		GrEmpl	
<10 years	6.39	7.04	36.57	19.42	21.57	13.07	13.22	5.39
10 to 19 years	15.57	15.20	16.98	15.85	12.10	13.11	2.88	2.80
20 to 29 years	24.85	25.01	14.86	12.53	9.64	10.51	2.74	0.01
30 or more	48.50	53.88	11.75	10.30	7.68	7.65	1.31	−0.33
Diff. means: Wilks' lambda (Prob > F)	0.4310 (0.000)		0.9993 (0.3308)		0.9993 (0.3341)		0.9701 (0.000)	

Source: Spanish PITEC.
Notes: Productivity = Sales per employee, Empl = number of employees, Sales = values of sales (in millions of euros), GrProd = annual growth rate of Sales per employee, GrEmpl = annual growth rate of employees, GrSales = annual growth rate of sales.

tory for firms in the sampling frame to answer the questionnaire, hence the response rate is high, and when they disappear this is generally because they have ceased operations. The dataset offers information of these events. The percentage of firms which at the end of the panel have exited is equal to 5%. The Spanish PITEC questionnaire is representative for Spanish innovating firms and, as a consequence, we have a set of firms with a larger propensity to innovate. The dataset contains SMEs and large firms. The database's sampling frame includes all innovative firms with more than 200 employees, while the sampling frame for firms with fewer than 200 employees is based on random selection among all firms in this smaller size category.

Spain provides an interesting context for our analysis for several reasons. First, Spain has a lower R&D intensity than many other European countries. This implies that our current analysis of the effects of R&D on firm growth is most relevant for the context of countries that are slightly lagging behind the world technological frontier. Our analysis of the effect of R&D on firm growth for firms of different ages provides new evidence on the incentives for firms to invest in R&D. Second, the critical situation of the Spanish economy motivates our analysis of the effect of R&D on firm growth as a way of enabling firms to boost their competitiveness and their capacity to create jobs. Third, given the scarce public resources available to support innovation, it is necessary to improve our understanding of heterogeneous innovation outcomes for firms in order to better design effective policies for supporting firm-level innovation.

Our data cleaning process involves, first, excluding firms for whom there is no information on their year of entry[1]; and second, excluding firms experiencing mergers or acquisitions.

Table 1 shows the descriptive statistics, broken down by firm age and R&D investment activity. Overall, 70% of observations correspond to firms that have invested in R&D.

Furthermore, we may highlight the following features. First, the average firm age for our categories (firms with less than 10 years, those 10–19 years, those 20–29 years, and firms with 30+ years) shows no significant differences depending on whether the firms are investing in R&D. However, firms that invest in R&D are generally (but not always) slightly younger, more productive and have larger sales. Second, concerning growth rates, there is a negative relationship between firm age and growth rates, with older age groups having lower growth rates (in line with much previous research). Finally, there appear some differences between the growth rates of firms investing in R&D and those that they do not invest. Firms investing in R&D activities have slightly higher growth rates regardless the growth variable.

Table 1 also includes Wilks' lambda tests of means by age group. Our results conclude that the means are significantly different between the age groups. The only exceptions are for our measures of sales growth and productivity growth.

A key variable in our analysis is firm age, and an inspection of the firm age distribution sheds light on the representativeness of our sample. Fig. A1 shows the age distribution for our whole sample (after cleaning the data). Previous work on the age distribution of firms suggests that the firm age distribution of the population of firms is approximately exponential (Coad, 2010b), which implies that the modal age should be the lowest age category, with the number of firms decreasing as age increases. Furthermore, the firm age distribution shows a long right tail indicating positive skewness. Our mode is 5–7 years and the average firm age is 23.67 years, which suggests that firms of age 0–4 are under-represented in our data. Indeed, young firms are often under-represented in firm-level databases (Headd and Kirchhoff, 2009; Coad et al., 2013), and this problem is presumably more severe for innovation data than for compulsory administrative data such as employee records. Furthermore, previous work on the relationship between age and innovation was performed on data where the modal age category is not the youngest age category, indicating that young firms are under-represented in available datasets on firm-level innovation (see e.g. Huergo and Jaumandreu, 2004a, their Fig. A1). Therefore, we will have to be cautious in interpreting the results for the age group of less than ten years.

In addition to the mean differences, in line with Cabral and Mata (2003) the density function is skewed towards the right (see Fig. A2 in Appendix A) and the skewness diminishes when considering older firms. Thus, young firms have lower (log) sales, (log) productivity (measured as sales per employee) and (log) employees in comparison with older firms that were active in the market in 2006, but that their size and productivity improve over time. Furthermore, Fig. A3 shows that firm growth dispersion decreases among the group of older firms[2].

[1] The 2009 wave provides information on age. Since we can track firms back in time from 2009, we are able to impute firm age for previous years.

[2] In this line, Fig. A2 shows a higher density around the growth rate equal to 0 for the oldest firms, regardless the variable. In that sense, younger firms show a lower density around the mode while there is a higher density on the right tail (showing a larger proportion of firms experiencing high growth rates).

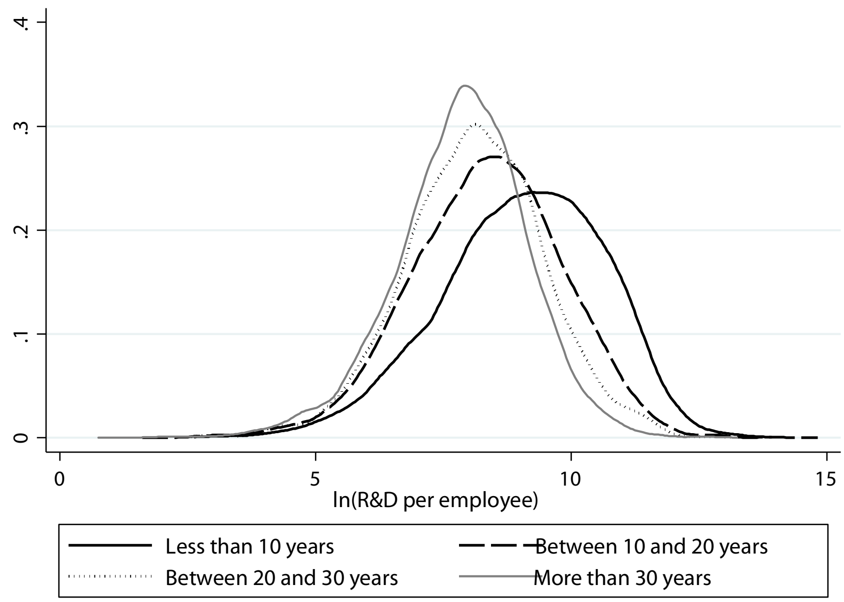

Fig. 1. Kernel density of ln(R&D investment per employee) in 2006.

Apart from the differences in firm performance according to firm age, Fig. 1 shows the kernel density of R&D investment for our four age groups. The distribution of R&D intensity evolves towards the left as firms age. Our evidence shows that young innovative firms have higher R&D intensity than older firms. On the one hand, this may confirm our theoretical framework where young firms make a larger R&D effort in order to introduce radical new innovations, to differentiate their products and to survive in the market. On the other hand, older firms invest less in R&D activities, perhaps because they are engaged in more incremental R&D activities that can be exploited alongside scale economies (i.e. large total amounts of R&D, but low intensities of R&D due to their larger scale).

5. Econometric methodology

In order to analyze the effect of R&D intensity on firm growth, we estimate the following equations:

$$\begin{aligned}\mathrm{GrSales}_{i,t} &= \alpha_{10} + \alpha_{11}\mathrm{LogSales}_{i,t-1} + \alpha_{12}\mathrm{GrEmpl}_{i,t} + \alpha_{13}\mathrm{GrInv}_{i,t} + \alpha_{14}\mathrm{RDintensity}_{i,t-1} \\ &\quad + \alpha_{15}\mathrm{Young}\times\mathrm{RDintensity}_{i,t-1} + \alpha_{16}\mathrm{Controls}_{i,t} + u_1 + \varepsilon_{1i,t}\end{aligned} \tag{1}$$

$$\begin{aligned}\mathrm{GrProd}_{i,t} &= \alpha_{20} + \alpha_{21}\mathrm{LogProd}_{i,t-1} + \alpha_{22}\mathrm{GrEmpl}_{i,t} + \alpha_{23}\mathrm{GrInv}_{i,t} + \alpha_{24}\mathrm{RDintensity}_{i,t-1} \\ &\quad + \alpha_{25}\mathrm{Young}\times\mathrm{RDintensity}_{i,t-1} + \alpha_{26}\mathrm{Controls}_{i,t} + u_2 + \varepsilon_{2i,t}\end{aligned} \tag{2}$$

$$\begin{aligned}\mathrm{GrEmpl}_{i,t} &= \alpha_{30} + \alpha_{31}\mathrm{LogEmpl}_{i,t-1} + \alpha_{32}\mathrm{GrInv}_{i,t} + \alpha_{33}\mathrm{RDintensity}_{i,t-1} \\ &\quad + \alpha_{34}\mathrm{Young}\times\mathrm{RDintensity}_{i,t-1} + \alpha_{35}\mathrm{Controls}_{i,t} + u_3 + \varepsilon_{3i,t}\end{aligned} \tag{3}$$

where α_i are the coefficients, u_i corresponds to the time-invariant firm-specific fixed effects, and ε_{it} is the usual error term for firm i at time t. The dependent variable is the annual growth rate of either employment, sales, or productivity (i.e. sales per employee). Firm growth rates are measured in terms of alternative growth indicators (that can be taken to reflect different facets of the growth process): employment growth (GrEmpl), productivity growth (measured as sales per employee, also known as 'labour revenue productivity', GrProd), and sales growth (GrSales). Annual firm growth rates are calculated in the usual way by taking log-differences of size (e.g. Tornqvist et al., 1985; Coad, 2009).

To control for the possibility that growth of sales and productivity may depend on the (simultaneous) growth of inputs, we control for growth of employment and growth of investment in Eqs. (1) and (2). Relatedly, in Eq. (3), we control for the possible influence of growth of investment on growth of employment. However, in further robustness analysis we verify that the main results hold whether or not we control for growth of these inputs (results available upon request).

The key explanatory variable of interest is the interaction term Young × RDintensity$_{i,t-1}$, which captures the specific effect of the R&D behaviour of young firms (i.e. less than 10 years old) over and above the average effects for all firms (of all ages). If R&D undertaken by young firms is different from R&D undertaken by more established firms, then this interaction term will be statistically significant.

Our other explanatory variables are described in Table 2, and Tables A1 and A2 contain descriptive statistics and correlations, respectively. Our control variable for firm age is measured in terms of the dummy variable 'Young', rather than including a continuous variable such as log(age), because of concerns that regression models with interaction terms should include all constitutive terms of the interaction (Brambor et al., 2006)[3]. Our choice of explanatory variables follows from previous work on the determinants of firm growth (see Coad, 2009 for a survey), as well as being restricted by the variables available to us in our dataset. We are not especially concerned about omitted variable bias in the present context, because the previous literature has not (yet) found any particular

[3] We are grateful to a reviewer for this suggestion. In a previous version, we included log(age) as a control alongside our interaction term 'Young × RDintensity', and obtained results that were overall similar.

Table 2
Description of the variables.

Variable	Description
RDintensity	R&D intensity measured as the logarithm of the amount of R&D investment per employee
LogSales, LogProd, LogEmpl	The natural log of size, measured in terms of sales, productivity (i.e. sales per employee), or number of employees. LogSales is included in Eq. (1), LogProd is included in Eq. (2) and LogEmpl is included in Eq. (3). Inclusion of these variables allows us to include lagged size as a control variable, which allows us to investigate dynamic convergence processes
GrInv	Annual growth of capital (machinery) investment, where growth rates are measured by taking log-differences
GrSales, GrProd, GrEmpl	Annual growth rate calculated by taking log-differences of the respective size levels
Cooperation	Dummy variable for R&D cooperation activity
Young	Dummy variable equal to 1 if the firm is aged less than 10 years; otherwise it is equal to 0. Age is measured as the difference between the current year and the year the firm registered to start business
Young × RDintensity	Interaction term whereby R&D intensity is multiplied by the dummy variable 'Young'
Exports	Percentage of exports with respect to total sales.
Concentration	Percentage of sales by firms with more than 250 employees.
Sectoral dummies	Sectoral dummies to control for common shocks at industrial level
Year dummies	Time dummies to control for common macroeconomic effects

variable that is capable of explaining firm growth rates to any large extent – instead growth rates appear to be difficult to predict and best approximated by a random walk (Geroski, 2000; Coad, 2009).

In order to estimate the effect of R&D intensity on firm performance, we apply quantile regression techniques. Quantile regression has been frequently applied to analyse issues related to the distribution of returns to innovation (Coad and Rao, 2006, 2008; Goedhuys and Sleuwaegen, 2009; Hölzl, 2009; Kaiser, 2009; Love et al., 2009; Ebersberger et al., 2010; Segarra and Teruel, 2011; Falk, 2012; Mata and Woerter, 2013; Bartelsman et al., 2014; Mazzucato and Parris, 2015; Capasso et al., 2015; Bianchini et al., 2015). In this paper, we apply quantile regression to investigate the distribution of the returns to innovation for subsamples of young and old firms. Quantile methods may be preferable to the more usual regression methods for other reasons. First, while conventional regressions focus on the average firm, quantile regression can describe the full (conditional) distribution of the dependent variable. This is an important feature, because we are less interested in the average effects of R&D on growth in this paper, but instead we are interested in the riskiness of young firm R&D as evidenced by heterogeneous effects across the growth rate distribution. Second, the standard least-squares assumption of normally distributed errors does not hold for our data because our dependent variables (firm growth rates) follow heavy-tailed distributions. Instead, quantile regression is robust to extreme observations on the dependent variable[4].

The quantile regression estimator was originally designed for the analysis of cross-sectional datasets (Koenker and Bassett, 1978). In recent times, however, theoretical developments in applying quantile regression to panel contexts have emerged (Koenker, 2004; Galvao, 2011; Canay, 2011). Whereas most of the literature investigating the firm-level performance benefits of innovation has applied cross-sectional quantile regression estimators (see however Bartelsman et al. (2014), Mazzucato and Parris (2015), and Bianchini et al. (2015) for exceptions), in our case we apply panel quantile regressions following Canay (2011). Panel quantile regressions will allow us to control for time-invariant firm-specific effects in order to better analyse the specific effect of R&D on subsequent firm growth.

Let us rewrite Eqs. (1)–(3) in more general form as:

$$y_{i,t} = x'_{i,t}\beta + u_i + \varepsilon_{i,t} \tag{4}$$

where $y_{i,t}$ is the outcome variable (i.e. growth rates) and $x_{i,t}$ corresponds to the explanatory variables (including R&D intensity). Canay's panel quantile regression estimator deals with the problem of estimating the fixed effects u_i by assuming that they are 'pure location shift parameters' that take the same values at all values along the quantiles of the growth rate distribution.

Our quantile regression procedure therefore proceeds in two steps (Canay, 2011). The first step involves estimating the unobserved time-invariant effects u_i, which is done by least-squares estimation (i.e. using usual fixed-effect regression) of equation [4]. Consider the conditional mean equation represented by (4), with $E(\varepsilon_{i,t} \mid x_i, u_i)$. This conditional mean equation implies that the firm-specific fixed effect u_i is present in the conditional mean of $y_{i,t}$. The estimated fixed effect $\hat{u}_i$ can then be estimated as $\hat{u}_i = E_T\left(y_{i,t} - x'_{i,t}\hat{\beta}\left(\theta\right)\right)$, where $\beta(\theta_\mu)$ is the vector of coefficients estimated from the first-stage conditional mean equation (which is estimated using conventional least-squares 'fixed-effects' panel regression), and where $\hat{\beta}\left(\theta_\mu\right)$ is a $\sqrt{nT}$ -consistent estimator of $\beta(\theta_\mu)$. Once the fixed effect $\hat{u}_i$ has been thus estimated, it is assumed to take the same values across the quantiles. The second step of Canay's estimator involves applying the well-known cross-sectional quantile regression estimator (due to Koenker and Bassett, 1978) on a new dependent variable $\hat{y}_{i,t}$ that has been created by transforming $y_{i,t}$ to remove the fixed-effect: $\hat{y}_{i,t} = y_{i,t} - \hat{u}_i \cdot$ $\hat{y}_{i,t}$ is then regressed on x'_{it}. The quantile regression results therefore refer to the quantiles of the time-varying error term ε_{it} once the influence of the time-invariant variable $\hat{u}_i$ has been controlled for. Further details on our panel quantile regression estimator are in Canay (2011). To ensure precision in our inference, we report bootstrapped standard errors (with 100 bootstrap replications).

The nature of innovation at the firm level is likely to be affected by endogeneity between innovative activities and firm growth. In other words, although innovation may lead to growth, firms that enjoy growth (or even firms that anticipate that they will grow) may be better able to commit resources to subsequent innovation activity (Coad and Rao, 2010). Using firm-level data from the CIS II, Cainelli et al. (2006) show for service firms that innovation is positively affected by past economic performance and that innovation activities have a positive effect on both growth and productivity. Problems of endogeneity may be alleviated by allowing for time lags between variables, and by controlling for the potentially confounding effects of time-invariant effects, but endogeneity cannot be completely ruled out in our case (Nichols, 2007). Furthermore, the severity of endogeneity may differ for small and large firms[5].

[4] See for example Fig. A2, where the growth rate distributions for sales, productivity, and employment are heavy-tailed, especially for younger firms.

[5] There may be many reasons why endogeneity might differ between small and large firms, two of which are mentioned here. First, endogeneity might differ between small and large firms if they operate on different time horizons (e.g. small firms are buffeted around by higher-frequency shocks, whereas large firms are more inert and their growth plans and strategies are carried out over a longer

Table 3
Fixed effects quantile regression estimates for sales growth (100 bootstrap replications).

	5% (1)	10% (2)	25% (3)	50% (4)	75% (5)	90% (6)	95% (7)
$LogSales_{t-1}$	−0.560***	−0.562***	−0.568***	−0.574***	−0.577***	−0.584***	−0.589***
	(0.0033)	(0.0019)	(0.0012)	(0.0009)	(0.0011)	(0.0023)	(0.0034)
$GrEmpl_t$	0.342***	0.327***	0.315***	0.321***	0.319***	0.293***	0.296***
	(0.0335)	(0.0209)	(0.0131)	(0.0075)	(0.0129)	(0.0195)	(0.0198)
$GrInv_t$	0.0023***	0.0013***	0.0007***	0.0007***	0.0005***	0.0005**	0.0008*
	(0.0005)	(0.0003)	(0.0002)	(0.0001)	(0.0002)	(0.0003)	(0.0004)
$RDintensity_{t-1}$	−0.0298***	−0.0197***	−0.0105***	−0.0036***	0.0038***	0.0069***	0.0122***
	(0.0038)	(0.0026)	(0.0012)	(0.0008)	(0.0012)	(0.0020)	(0.0030)
Young × $RDintensity_{t-1}$	−0.0687***	−0.0424***	−0.0223***	−0.0081***	0.0072**	0.0381***	0.0590***
	(0.0100)	(0.0045)	(0.0031)	(0.0021)	(0.0031)	(0.0061)	(0.0105)
$Young_t$	0.365***	0.233***	0.116***	0.0344**	−0.0583**	−0.259***	−0.369***
	(0.0714)	(0.0348)	(0.0254)	(0.0170)	(0.0266)	(0.0459)	(0.0811)
$Cooperation_{t-1}$	−0.0010	0.0051	0.0033	0.0119***	0.0126***	0.0228***	0.0370***
	(0.0117)	(0.0067)	(0.0036)	(0.0024)	(0.0033)	(0.0059)	(0.0093)
$Exports_{t-1}$	0.108***	0.0742***	0.0718***	0.0748***	0.0715***	0.0751***	0.0779***
	(0.0190)	(0.0127)	(0.0066)	(0.0049)	(0.0078)	(0.0129)	(0.0180)
$Concentration_{t-1}$	−0.0005***	−0.0005***	−0.0005***	−0.0005***	−0.0006***	−0.0007***	−0.0005***
	(0.0001)	(7.57e − 05)	(4.82e − 05)	(3.27e − 05)	(4.80e − 05)	(0.0001)	(0.0002)
Constant	8.773***	8.854***	9.057***	9.235***	9.354***	9.577***	9.705***
	(0.0716)	(0.0438)	(0.0238)	(0.0174)	(0.0241)	(0.0466)	(0.0710)
Pseudo-R2	0.7257	0.7575	0.7886	0.8016	0.7888	0.7578	0.7282
Observations				26,600			

Time and sectoral dummies are included. Standard errors in parentheses.
*** $p < 0.01$.
** $p < 0.05$.
* $p < 0.1$.

Bearing in mind this possible endogeneity between firm growth and R&D investment, therefore, we cannot claim to have identified causal effects, but instead we merely seek to report interesting associations on the relationship between R&D investment and firm growth, for firms of different ages[6].

6. Results

6.1. Innovation and firm performance: Quantile estimations

Tables 3–5 present our regression quantile results for the quantiles θ = 0.05, 0.10, 0.25, 0.50, 0.75, 0.90 and 0.95. Quantile regression coefficients can be interpreted as the marginal change in y at the θth conditional quantile caused by marginal change in a particular regressor, $\Delta Q_\theta\ (y_i|x_i)/\Delta x$. Quantile estimators will lead us to assess the effect of innovation across the conditional distribution of the dependent variable (firm growth). As we will see, we obtain different results depending on the quantiles.

Our main variable of interest is the interaction term Young × $RDintensity_{i,t-1}$, which captures the effect of young firm R&D over and above the main effect of R&D for all firms. Young firm R&D is positively associated with sales growth at the upper quantiles, but negatively associated with sales growth at the lower quantiles (Table 3). Indeed, R&D investment does not always result in superior performance (Demirel and Mazzucato, 2012; Nunes et al., 2012). Our results suggest that successful R&D investments may be associated with subsequent sales growth, but that unsuccessful R&D investments are associated with subsequent sales decline. Hence, young firm R&D is especially risky – it may result in either faster growth or faster decline. Table 4 shows a similar pattern for productivity growth – young firm R&D has larger upside gains but larger downside losses. Table 5 also shows a similar pattern whereby the effect of Young × $RDintensity_{i,t-1}$ increases across the quantiles, with negative effects at the lower end of the distribution.

Fig. 2 provides a graphical representation of our main regression results. The effects of Young × $RDintensity_{i,t-1}$ on firm growth increase across the quantiles, starting from negative values at the lower quantiles (in the cases of sales growth and productivity growth) and reaching relatively large positive values at the upper quantiles (in all three cases: sales growth, productivity growth and employment growth).

As a consequence, our Hypotheses 1a and 1b find support. On the one hand, young firms that achieve higher growth rates are positively affected by investment in R&D activities, in support of Hypothesis 1a. On the other hand, those firms with low growth rates are negatively affected by R&D investment, which is in accord with Hypothesis 1b. R&D investment undertaken by young firms appears to be a double-edged sword that amplifies the upside gains and downside losses—either it can lead to large performance benefits (as indicated by the positive effects at the upper quantiles), or else it can lead to large losses (as indicated by the negative effects at the lower quantiles). Youth therefore increases the riskiness of R&D investment. Furthermore, our results may be complementary to Cincera and Veugelers (2014). Those authors find that European YICs generate lower significant rates of return than US YICs. Despite this evidence, our results show that Spanish successful young innovative firms are able to grow more than mature firms.

Hypothesis 1 is supported in the cases of employment and productivity growth, although not for sales growth. The panel quantile regression results, evaluated at the median (i.e. the 50% quantile), indicate a significant negative effect of R&D intensity on the growth of sales (Table 3), whether we look at R&D of the full sample of firms or the interaction term that relates to the subsample of young firms. In the case of employment growth (and to a lesser extent for

time horizon, perhaps because they have 'deeper pockets' that allow them to undertake longer R&D projects). Second, endogeneity might differ between small and large firms because small firms might be more financially constrained, and the availability of funds for R&D might be affected by the growth of profits that occurs via growth of sales or growth of productivity. Hence, there might be greater feedback from growth to R&D expenditure in smaller firms.

[6] We have also investigated the existence of reverse causality applying a Granger causality test. Controlling for all the explanatory variables, our results show that R&D per employee Granger-causes firm growth regardless the measure of firm size, while firm growth only Granger-causes R&D per worker in one case (sales growth, at a critical p-value of 10%). We are grateful to an anonymous referee for this suggestion.

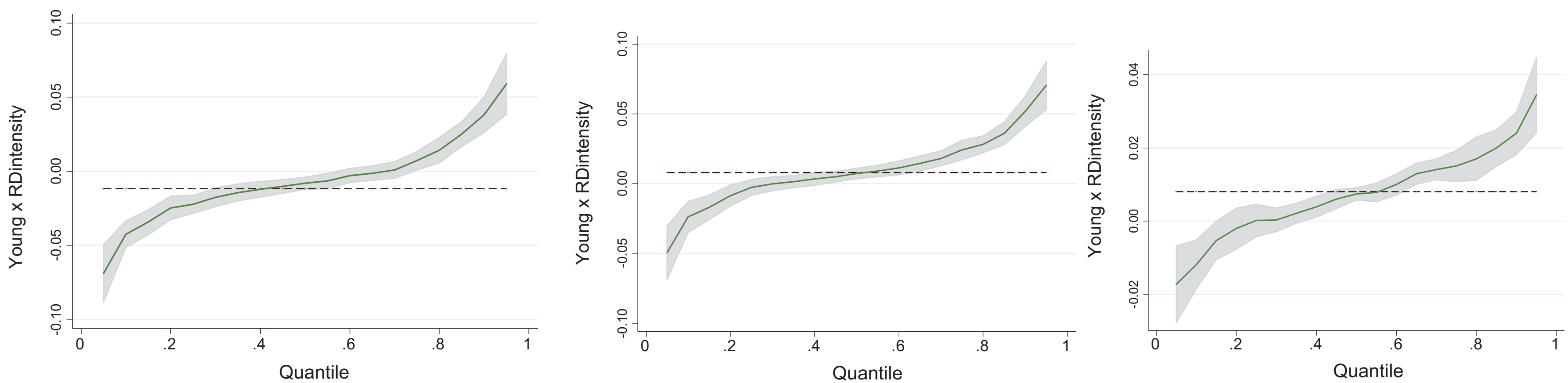

Fig. 2. Quantile regression plots. Effects of the interaction term Young × RDintensity$_{i,t-1}$ (see Eqs. (1)–(3)) on firm growth (i.e. growth of sales (left), growth of productivity (centre), and growth of employment (right)).

Table 4
Fixed effects quantile regression estimates for productivity growth (100 bootstrap replications).

	5% (1)	10% (2)	25% (3)	50% (4)	75% (5)	90% (6)	95% (7)
$LogProd_{t-1}$	−0.686***	−0.682***	−0.687***	−0.697***	−0.700***	−0.710***	−0.719***
	(0.0073)	(0.0039)	(0.0025)	(0.0018)	(0.0025)	(0.0047)	(0.0056)
$GrEmpl_t$	−0.336***	−0.342***	−0.343***	−0.353***	−0.373***	−0.399***	−0.395***
	(0.0353)	(0.0170)	(0.0119)	(0.0065)	(0.0111)	(0.0156)	(0.0219)
$GrInv_t$	0.0019***	0.0012***	0.0006***	0.0007***	0.0004*	0.0007**	0.0012***
	(0.0005)	(0.0003)	(0.0002)	(0.0001)	(0.0002)	(0.0003)	(0.0004)
$RDintensity_{t-1}$	−0.0191***	−0.0065***	0.0031***	0.0108***	0.0176***	0.0279***	0.0371***
	(0.0038)	(0.0022)	(0.0012)	(0.0008)	(0.0012)	(0.0021)	(0.0031)
Young × $RDintensity_{t-1}$	−0.0495***	−0.0239***	−0.0027	0.0072***	0.0240***	0.0517***	0.0704***
	(0.0098)	(0.0057)	(0.0029)	(0.0019)	(0.0036)	(0.0055)	(0.0088)
$Young_t$	0.243***	0.106**	−0.0173	−0.0712***	−0.176***	−0.349***	−0.442***
	(0.0726)	(0.0457)	(0.0245)	(0.0161)	(0.0299)	(0.0396)	(0.0665)
$Cooperation_{t-1}$	−0.0065	−0.0061	−0.0018	0.0018	0.0035	0.0032	0.0177*
	(0.0113)	(0.0058)	(0.0029)	(0.0023)	(0.0033)	(0.0058)	(0.0098)
$Exports_{t-1}$	0.0215	0.0139	0.0099*	0.0230***	0.0083	0.0295**	0.0292
	(0.0207)	(0.0124)	(0.0053)	(0.0050)	(0.0076)	(0.0148)	(0.0195)
$Concentration_{t-1}$	−0.0006***	−0.0006***	−0.0007***	−0.0007***	−0.0007***	−0.0008***	−0.0006***
	(0.0001)	(8.33e − 05)	(5.08e − 05)	(3.57e − 05)	(4.95e − 05)	(0.0001)	(0.0002)
Constant	7.901***	7.879***	8.023***	8.193***	8.291***	8.461***	8.599***
	(0.0906)	(0.0517)	(0.0311)	(0.0228)	(0.0318)	(0.0589)	(0.0723)
Pseudo-R2	0.5688	0.6126	0.6560	0.6751	0.6698	0.6455	0.6264
Observations				26,600			

Time and sectoral dummies are included. Standard errors in parentheses.
*** $p < 0.01$.
** $p < 0.05$.
* $p < 0.1$.

productivity growth) Hypothesis 1 is supported, because the R&D intensity of the full sample of firms is positively associated with growth of employment or productivity, and this positive effect is further augmented by positive and significant interaction term for the subsample of young firms. Hence, R&D investment by young firms appears to be more 'labour-friendly' than R&D investment by more mature firms, in the sense that it is more positively associated with employment growth. This is an interesting finding that further bolsters the interest of policy-makers in supporting the R&D investment of young firms. Young firms have been observed to make a large contribution to job creation (Haltiwanger et al., 2013; Lawless, 2014; Hyytinen and Maliranta, 2013), and this appears to be especially true for young innovative firms.

Our regression results in Tables 3–5 also reveal some other interesting results concerning the determinants of growth. Lagged size is negatively associated with subsequent growth (and we suspect that the large magnitudes of these effects are related to our choice of fixed-effects regression framework). Employment growth contributes positively to sales growth (Table 3) and contributes negatively to productivity growth (Table 4). Investment growth is positively associated with growth of sales and productivity (Tables 3 and 4). The three tables show that the 'Young' dummy variable is negatively associated with growth at the lower quantiles, and positively associated with growth at the upper quantiles. Sales growth appears to be positively related to exporting, but negatively related to concentration (Table 3). Productivity growth is also neg-

Table 5
Fixed effects quantile regression estimates for employment growth (100 bootstrap replications).

	5% (1)	10% (2)	25% (3)	50% (4)	75% (5)	90% (6)	95% (7)
$LogEmpl_{t-1}$	−0.332***	−0.337***	−0.343***	−0.347***	−0.349***	−0.354***	−0.357***
	(0.0023)	(0.0016)	(0.0008)	(0.0005)	(0.0007)	(0.0013)	(0.0017)
$GrInv_t$	0.0010***	0.0006***	0.0005***	0.0004***	0.0004***	0.0003*	0.0001
	(0.0003)	(0.0002)	(0.0001)	(4.42e − 05)	(0.0001)	(0.0002)	(0.0003)
$RDintensity_{t-1}$	0.0053**	0.0084***	0.0093***	0.0126***	0.0150***	0.0175***	0.0205***
	(0.0026)	(0.0015)	(0.0007)	(0.0004)	(0.0006)	(0.0011)	(0.0017)
Young × $RDintensity_{t-1}$	−0.0172***	−0.0119***	0.0002	0.0074***	0.0151***	0.0240***	0.0345***
	(0.0054)	(0.0034)	(0.0022)	(0.0009)	(0.0022)	(0.0030)	(0.0052)
$Young_t$	0.0556	0.0363	−0.0300	−0.0669***	−0.103***	−0.144***	−0.204***
	(0.0453)	(0.0284)	(0.0195)	(0.0070)	(0.0187)	(0.0253)	(0.0430)
$Cooperation_{t-1}$	0.0047	−0.0009	0.0046**	0.0027***	0.0026	0.0017	0.0016
	(0.0052)	(0.0030)	(0.0018)	(0.0009)	(0.0017)	(0.0035)	(0.0054)
$Exports_{t-1}$	0.0757***	0.0521***	0.0230***	0.0202***	0.0129***	−0.0022	−0.0142
	(0.0098)	(0.0077)	(0.0037)	(0.0023)	(0.0041)	(0.0084)	(0.0117)
$Concentration_{t-1}$	0.0001	0.0002**	0.0001***	3.56e − 05**	−4.65e − 05*	−0.0002***	−0.0002**
	(7.55e − 05)	(6.21e − 05)	(3.09e − 05)	(1.54e − 05)	(2.59e − 05)	(4.71e − 05)	(8.64e − 05)
Constant	1.021***	1.132***	1.252***	1.307***	1.352***	1.430***	1.492***
	(0.0320)	(0.0177)	(0.00812)	(0.0048)	(0.0067)	(0.0130)	(0.0200)
Pseudo-R2	0.6896	0.7171	0.7542	0.7677	0.7469	0.7062	0.6731
Observations				26,612			

Time and sectoral dummies are included. Standard errors in parentheses.
*** $p < 0.01$.
** $p < 0.05$.
* $p < 0.1$.

atively related to concentration (Table 4). Exporting is positively related to employment growth in Table 5 (although this effect fades away at the upper quantiles).

6.2. Alternative indicators of the radicalness of innovation

To further investigate how the nature of innovation changes with firm age (i.e. whether old firms in our sample are more likely to perform incremental innovations, while young firm are more prone to develop radical innovations), we investigate alternative indicators of the radicalness of innovation, that comes from responses to survey questions that are available in our database. Table 6 below presents evidence on firms' responses during the period 2004–2012. The first row contains information on the percentage of firms that declared to have introduced products that are new to the market (which can be taken as an indicator of radical innovation). The results show that younger firms (up to 10 years) are much more likely to introduce products new to the market (i.e. engage in radical innovation), although the effects are not monotone across older age categories. The second row shows the percentage of firms that declared to have introduced products that are new to the firm (which can be an indicator of incremental innovation or imitation). The results show that younger firms are less likely to introduce products new to the firm. The third row shows that young firms have a larger share of their sales coming from radical innovation (i.e. sales new to the market). The fourth row contains information on incremental innovation (share of sales new to the firm but not new to the market), which takes higher values for younger firms, and decreases monotonically across age categories[7]. Taken together, these first four rows show that firms in the youngest age category are more likely to engage in radical innovation, although the results for incremental innovation are less clear, and the effects are not monotone across older age categories.

The two lower rows of Table 6 present information on the percentages of firms that abandoned an innovation project, for different age categories. We distinguish between projects that were abandoned during the project conception stage, and projects that were abandoned once they had been started. The riskiness involved in these innovative projects may arguably shed light on their radicalness, if we consider that radical innovative projects are marked by uncertainty whereas more incremental R&D projects are more predictable and less likely to be abandoned. (An alternative explanation, however, would be that the abandonment of R&D projects is undertaken more often by more experienced firms, with larger project portfolios, who are better able to spot the early warning signs that R&D projects are likely to disappoint and they can cut their losses earlier.) These last two rows of Table 6 suggest that firms in the youngest age category are more likely to abandon their innovative projects than firms in the next two age categories, although, interestingly enough, firms in the oldest age category are the most likely to abandon their innovative projects. Indeed, the non-monotonic relationship observed across age categories in the last two rows may indicate that the phenomenon is not straightforward, and that more than one effect may be at play.

6.3. Robustness

To investigate concerns about the time lags involved in the relationship between investment in innovation and performance benefits, we also repeated the analysis with a

[7] See also Aschhoff and Schmidt (2008, p56), who observe that "younger firms have larger shares of sales due to product imitations" in their innovation survey of German firms.

Table 6
Survey evidence on firms for the period 2004–2012. Percentage of firms introducing products new to the markets, percentage of firms introducing products new to the firm, percentage of sales due to innovations new to the market, percentage of sales due to innovations new to the firm, and percentage of firms that declare that they abandon an innovation project (either during the planning stage or once they started).

	Up to 10 years	From 11 to 20 years	From 21 to 30 years	More than 30 years	Mean(1)–Mean(2)		Mean(2)–Mean(3)		Mean(3)–Mean(4)	
					Ha: diff < 0	Ha: diff > 0	Ha: diff < 0	Ha: diff > 0	Ha: diff < 0	Ha: diff > 0
% Firms introducing products new to the market	61.5%	56.7%	55.6%	57.7%	1.000	0.000	0.895	0.104	0.006	0.993
% Firms introducing products new to the firm	73.03%	77.19%	78.42%	78.74%	0.000	1.000	0.042	0.958	0.321	0.679
% Sales due to products new to the market	14.2%	9.5%	9.0%	8.1%	1.000	0.000	0.955	0.045	0.999	0.000
% Sales due to products new to the firm	16.1%	13.6%	14.0%	12.7%	1.000	0.000	0.134	0.866	0.999	0.000
% Firms which abandon an innovation project during its conception	18.1%	16.1%	16.1%	19.7%	0.999	0.000	0.479	0.521	0.000	1.000
% Firms which abandon an innovation project once it has been started.	15.1%	14.0%	14.2%	17.1%	0.986	0.013	0.308	0.692	0.000	1.000

Source: our elaboration

cross-section of firms where R&D intensity was measured over the period 2005–2007, and growth was measured over the period 2007–2009. Focusing on this longer cross-section considerably reduces the number of observations, although it gives us a smoother growth indicator (because erratic growth rates are now smoothed over the three-year period). Our results are generally similar—for young firms the magnitude of the coefficient on R&D intensity increases across the quantiles, while for old firms there is a stable or possibly decreasing effect across the quantiles. (However, in many cases our estimates are not significant, no doubt because of the smaller number of observations.)

In our main estimations, we consider young firms as those aged less than 10 years. In further analysis, not reported here, we took an alternative cut-off threshold according to which 'young' firms were less than 15 years old, and obtained similar results[8]. We also explored whether the inclusion of a lagged dependent variable (i.e. lagged growth rate) affected our results. Although the lagged dependent variable was significant at some quantiles, nevertheless it did not change the pattern of results obtained for our main explanatory variable of interest, $\text{Young} \times \text{RDintensity}_{i,t-1}$. We repeated our panel quantile regression estimations excluding the lagged size levels, and obtained similar results. Finally, we also replaced our panel quantile regressions with standard Koenker and Bassett (1978)-style quantile regressions, and obtained similar findings.

7. Conclusions

The main objective of this article was to analyse the moderating role of age on the relationship between R&D investment and firm growth. Although there is previous theoretical and empirical literature trying to explain the heterogeneous innovative behaviour of firms according to firm age, few studies have analysed the influence of firm age on the relationship between R&D investment and firm growth.

Our results show that, for young firms, the effect of R&D on firm growth increases across the quantiles (from being negative at the lower quantiles to being positive at the upper quantiles), while the effects of R&D on growth are more stable for old firms. This suggests that innovation undertaken by young firms is riskier and the returns are unevenly distributed, while the innovation efforts of older firms are more predictable.

With regards to policy implications, it seems that young firms have particular innovation challenges, and that they engage in riskier R&D, although over time the returns to R&D become more predictable. Furthermore, innovation by younger firms is more likely to be associated with employment growth. To deal with this, we might think of making R&D support (subsidies, tax breaks, etc) conditional on firm age—focused more strongly on young firms, with older firms being less eligible for this support. However, this policy recommendation certainly needs further investigation before being acted upon, because we first need to improve our understanding of why young firm R&D is associated with risky outcomes[9].

Why could it be that young firms have a riskier profile of returns from R&D? There are several possible reasons. First, it could be because older firms undertake incremental innovation efforts along established trajectories that are less risky. Second, older firms may have learnt to spot earlier which R&D projects are likely to fail, and terminate them earlier. Third, it could be because older (larger) firms have a more diversified portfolio of R&D projects, which reduces the uncertainty of their total R&D activity. Fourth, our results could partly be explained by the possibility that performance indicators for young firms are more volatile in general (e.g. if young firms have a more dispersed growth rates distribution, Coad et al., 2013), and that as time goes by a firm's volatility decreases. Future work could fruitfully try to distinguish between these reasons. Finally, we suggest that future work (on richer data) would benefit from taking a finer-grained look at firm age, instead of looking at broad age groups—provided there are sufficient observations for each age group. Future work could also benefit from the analysis of innovation datasets with comprehensive coverage of the population of young firms (although here we acknowledge that we must probably wait for the 'next generation' of innovation datasets).

Further research could also try to shed further light on the ways in which the nature of innovation changes along the firm life course. In a recent paper, Criscuolo et al. (2012, p. 331) urge that "researchers should examine differences in the 'radicalness' of innovation developed by start-ups." Although we have not explicitly measured the radicalness of innovation in our dataset, nevertheless our findings are consistent with the suggestion that young firms engage in more radical innovation than mature firms, because the returns to innovation are more skewed. Nevertheless, we suggest that future work could fruitfully investigate how the nature of innovation (radical vs incremental, as well as product vs process) changes with firm age.

Acknowledgements

We are very much indebted to Tommaso Ciarli, Werner Hölzl, Jackie Krafft, Mariana Mazzucato, Rafael Myro, Mauro Napoletano, Paul Nightingale, Gabriele Pellegrino, Francesco Rentocchini, Maria Savona, Nick von Tunzelmann, as well as Keld Laursen (the editor) and several anonymous referees, and participants at SPRU seminar (15th May 2012), the Workshop on "Firm Growth and Innovation" (Tarragona 28th–29th June 2012), 2012 International Conference "The Governance of a Complex World" (Nice, 1st–3rd November 2012), and CONCORDi 2015 (JRC-IPTS, Seville, 1–2 October 2015. Alex Coad gratefully acknowledges financial support from the ESRC, TSB, BIS and NESTA on grants ES/H008705/1 and ES/J008427/1 as part of the IRC distributed projects initiative, as well as from the AHRC as part of the FUSE project. Agustí Segarra and Mercedes Teruel thank the Spanish Ministry of Industry, Tourism and Trade for financial support. This paper is part of the research done with the financial support of the Ministry of Innovation and Science (project ECO2009-08735) and the Consolidated Group of Research 2009-SGR-907. We are grateful to Verònica Gombau for her research support. The views expressed are purely those of the authors and may not in any circumstances be regarded as stating an official position of the European Commission. The usual disclaimer applies.

Appendix A.

Figs. A1–A3 and Tables A1 and A2

[8] We are grateful to an anonymous referee for suggesting that we define young firms as less than 10 years old.

[9] There may also be risks associated with policy interventions that seek to target young firms only. First, young firms have particularly high death rates, that level off after about 5 years (Anyadike-Danes and Hart, 2014), which might suggest that policy interventions should only target firms aged 5 or above. Second, policy interventions should avoid creating unnecessary churn, whereby viable firms are prematurely dissolved and then started up again with the same resources, in order to qualify for the support for young firms.

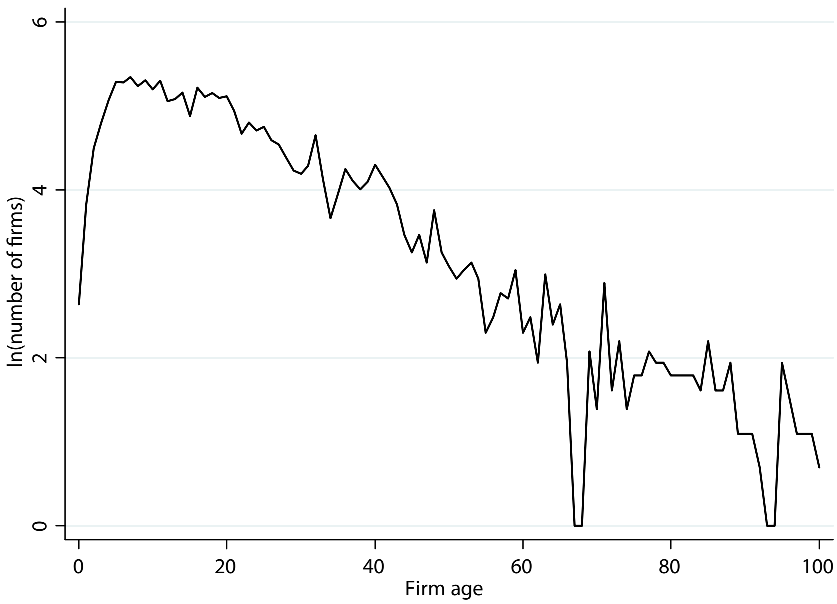

Fig. A1. Firm age distribution in 2005.

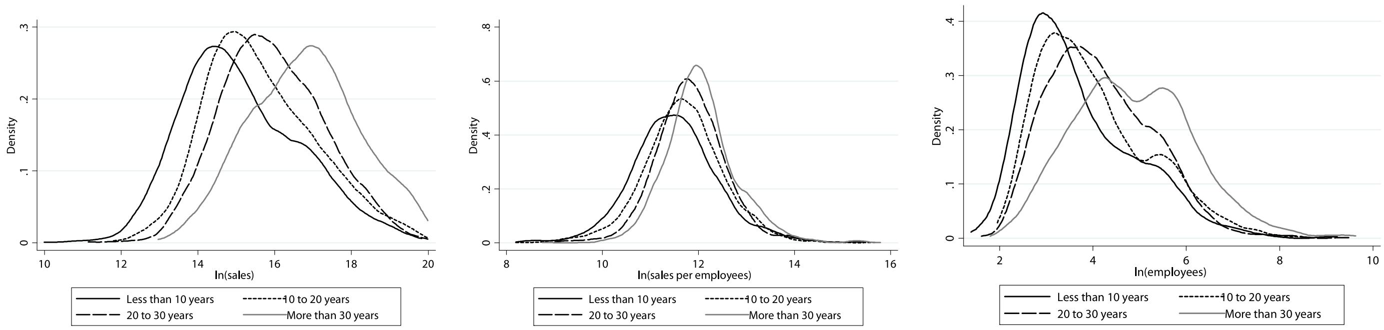

Fig. A2. Kernel density of log(sales) (left), log(productivity) (centre) and log(employees) (right) in 2005.

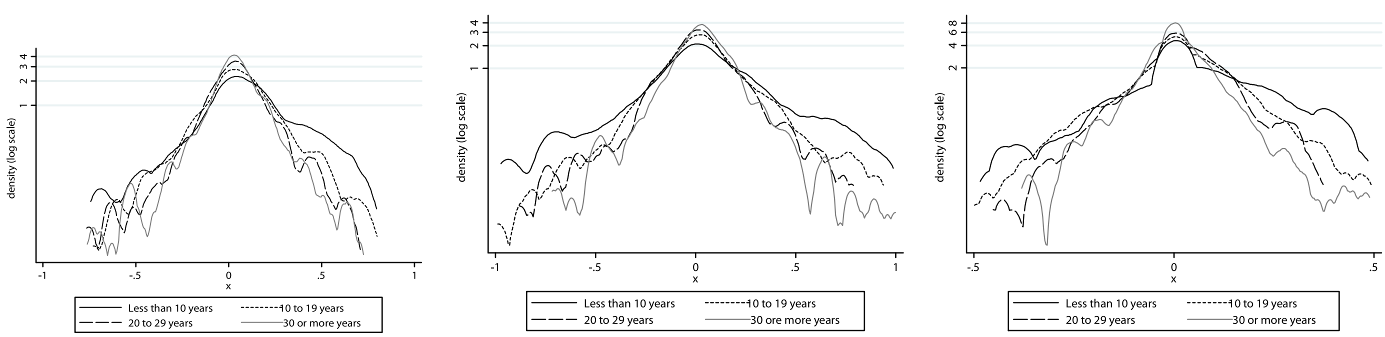

Fig. A3. Kernel density of growth of sales (left), growth of productivity (centre) and growth of employees (right) in 2006 for firms investing in R&D.

Table A1
Descriptive statistics.

	Mean	Median	Standard deviation	Minimum	Maximum
Sales growth	0.018	0.031	0.423	−10.439	11.508
Productivity growth	−0.001	0.001	0.418	−11.330	11.737
Employment growth	−0.002	0.000	.194	−3.219	2.613
Sales (lagged)	16.045	16.006	1.905	0.000	23.268
Productivity (Sales/Empl) (lagged)	11.923	11.937	0.904	−1.641	17.284
Number of Employees (lagged)	4.163	4.060	1.413	0.000	9.994
Investment growth (lagged)	−0.699	0.000	9.154	−31.476	33.327
RDintensity (lagged)	8.214	8.216	1.495	0.025	14.823
Young × RDintensity (lagged)	1.526	0.000	3.441	0.000	13.913

Table A1 (*Continued*)

	Mean	Median	Standard deviation	Minimum	Maximum
Young	0.170	0.000	0.375	0.000	1.000
Cooperation (lagged)	0.415	0.000	0.493	0.000	1.000
Exports (lagged)	0.139	0.025	0.217	0.000	1.000
Concentration (lagged)	35.860	22.800	309.760	3.000	646.460

Note: 26660 observations. *Source*: own elaboration.

Table A2
Matrix of Pearson correlations.

		(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)	(13)
(1)	Sales gr	1.000												
(2)	Prod. Gr	0.889*	1.000											
(3)	Empl. Gr	0.251*	−0.215*	1.000										
(4)	Log Sales (lagged)	−0.124*	−0.117*	−0.032*	1.000									
(5)	Log prod (lagged)	−0.215*	−0.255*	0.051*	0.709*	1.000								
(6)	Log Empl (lagged)	−0.024*	0.007	−0.072*	0.895*	0.321*	1.000							
(7)	Inv. growth	0.043*	0.022*	0.045*	0.033*	0.019*	0.034*	1.000						
(8)	RDintensity (lagged)	0.041*	0.001	0.107*	−0.320*	−0.137*	−0.349*	−0.018*	1.000					
(9)	Young x RDintensity (lagged)	0.087*	0.035*	0.124*	−0.342*	−0.244*	−0.305*	−0.003	0.318*	1.000				
(10	Young	0.083*	0.036*	0.110*	−0.313*	−0.227*	−0.275*	−0.002	0.237*	0.981*	1.000			
(11)	Cooperation (lagged)	0.031*	0.011	0.051*	0.120*	0.008	0.153*	0.028*	0.188*	0.072*	0.052*	1.000		
(12)	Exports (lagged)	0.047*	0.034*	0.016*	0.145*	0.140*	0.115*	0.008	0.024*	−0.075*	−0.076*	0.037*	1.000	
(13)	Concentration (lagged)	0.019*	0.008	0.016*	0.329*	0.308*	0.246*	0.012*	−0.035*	−0.078*	−0.072*	0.050*	0.030*	1.000

Source: own elaboration.
* Significant at 5%.

References

Acemoglu, D., Akcigit, U., Bloom, N., Kerr, W., April, 2013. Innovation, Reallocation and Growth. Harvard University, Cambridge (MA), USA.

Akcigit, U., Kerr, W.R., 2010. Growth through heterogeneous innovations. In: NBER Working Paper 16443, ⟨http://www.nber.org/papers/w16443⟩.

Anyadike-Danes, M., Hart, M., 2014. All Grown Up? The Fate After 15 Years of the Quarter of a Million UK firms Born in 1998. Mimeo, Aston Business School, Birmingham, Nov 14th.

Argote, L., 1999. Organizational Learning: Creating, Retaining and Transferring Knowledge. Kluwer Academic Publishers, Norwell, MA.

Aschhoff, B., Schmidt, T., 2008. Empirical evidence on the success of R&D cooperation—happy together? Rev. Ind. Organ. 33, 41–62.

Audretsch, D.B., Segarra, A., Teruel, M., 2014. Why not all young firms invest in R&D. Small Bus. Econ. 43 (4), 751–766.

Balasubramanian, N., Lee, J., 2008. Firm age and innovation. Ind. Corp. Change 17 (5), 1019–1047.

BarNir, A., Gallaugher, J.M., Auger, P., 2003. Business process digitization, strategy, and the impact of firm age and size: the case of the magazine publishing industry. J. Bus. Venturing 18, 789–814.

Barron, D.N., West, E., Hannan, M.T., 1994. A time to grow and a time to die: growth and mortality of credit unions in New York, 1914–1990. Am. J. Sociol. 100 (2), 381–421.

Bartelsman, E., Dobbelaere, S., Peters, B., 2014. Allocation of human capital and innovation at the frontier: firm-level evidence on Germany and the Netherlands. Ind. Corp. Change, http://dx.doi.org/10.1093/icc/dtu038.

Bartelsman, E., Scarpetta, S., Schivardi, F., 2005. Comparative analysis of firm demographics and survival: evidence from micro-level sources in OECD countries. Ind. Corp. Change 14 (3), 365–391.

Bianchini, S., Pellegrino, G., Tamagni, F., 2015. Innovation strategies and firm growth: new longitudinal evidence from spanish firms. In: Paper Presented at the 2015 DRUID Conference, June 15–17, 2015, Rome.

Brambor, T., Clark, W.R., Golder, M., 2006. Understanding interaction models: improving empirical analyses. Polit. Anal. 14, 63–82.

Cabral, L.M.B., Mata, J., 2003. On the evolution of the firm size distribution: facts and theory. Am. Econ. Rev. 93 (4), 1075–1090.

Cainelli, G., Evangelista, R., Savona, M., 2006. Innovation and economic performance in services: a firm-level analysis. Cambridge J. Econ. 30, 435–458.

Canay, I.A., 2011. A simple approach to quantile regression for panel data. Econometrics J. 14, 368–386.

Capasso, M., Treibich, T., Verspagen, B., 2015. The medium-term effect of R&D on firm growth. Small Bus. Econ. 45, 39–62.

Cincera, M., Veugelers, R., 2014. Differences in the rates of return to R&D for European and US young leading R&D firms. Res. Policy 43, 1413–1421.

Coad, A., 2009. The Growth of Firms: a Survey of Theories and Empirical Evidence. Edward Elgar, Cheltenham, UK.

Coad, A., 2010a. Exploring the processes of firm growth: evidence from a vector autoregression. Ind. Corp. Change 19 (6), 1677–1703.

Coad, A., 2010b. The exponential age distribution and the Pareto firm size distribution. J. Ind. Compet. Trade 10 (3), 389–395.

Coad, A., Rao, R., 2006. Innovation and market value: a quantile regression analysis. Econ. Bull. 15 (13), 1–10.

Coad, A., Rao, R., 2008. Innovation and firm growth in high-tech sectors: a quantile regression approach. Res. Policy 37 (4), 633–648.

Coad, A., Rao, R., 2010. Firm growth and R&D expenditure. Econ. Innov. New Technol. 19 (2), 127–145.

Coad, A., Reid, A., 2012. The role of technology and technology-based firms in economic development: rethinking innovation and enterprise policy in Scotland. In: Report for Scottish Enterprise.

Coad, A., Segarra, A., Teruel, M., 2013. Like milk or wine: does firm performance improve with age? Struct. Change Econ. Dynam. 24, 173–189.

Crepon, B., Duguet, E., Mairesse, J., 1998. Research, innovation and productivity: an econometric analysis at the firm level. Econ. Innov. New Technol. 7, 115–158.

Criscuolo, P., Nicolaou, N., Salter, A., 2012. The elixir (or burden) of youth? Exploring differences in innovation between start-ups and established firms. Res. Policy 41, 319–333.

Cucculelli, M., 2014. Firm age and the probability of product innovation. Do CEO tenure and product tenure matter? In: Mimeo, Paper Presented at the Governance of a Complex World Conference, Turin, Italy.

Czarnitzki, D., Delanote, J., 2013. Young innovative companies: the new high-growth firms? Ind. Corp. Change 22 (5), 1315–1340.

Czarnitzki, D., Kraft, K., 2004. An empirical test of the asymmetric models on innovative activity: who invests more into R&D, the incumbent or the challenger? J. Econ. Behav. Organ. 54, 153–173.

Dachs, B., Peters, B., 2014. Innovation, employment growth, and foreign ownership of firms: a European perspective. Res. Policy 43, 214–232.

Daunfeldt, S.-O., Elert, N., Johansson, D., 2015. Are high-growth firms overrepresented in high-tech industries? Ind. Corp. Change, http://dx.doi.org/10.1093/icc/dtv035, in press.

Decker, R., Haltiwanger, J., Jarmin, R., Miranda, J., 2014. The role of entrepreneurship in US Job Creation and Economic Dynamism. J. Econ. Perspect. 28 (3), 3–24.

Demirel, P., Mazzucato, M., 2012. Innovation and firm growth: is R&D worth it? Ind. Innov. 19 (1), 45–62.

Ebersberger, B., Marsili, O., Reichstein, T., Salter, A., 2010. Into thin air: using a quantile regression approach to explore the relationship between R&D and innovation. Int. Rev. Appl. Econ. 24 (1), 95–102.

Falk, M., 2012. Quantile estimates of the impact of R&D intensity on firm performance. Small Bus. Econ. 39 (1), 19–37.

Galvao, A.F., 2011. Quantile regression for dynamic panel data with fixed effects. J. Econometrics 164 (1), 142–157.

García-Quevedo, J., Pellegrino, G., Vivarelli, M., 2014. R&D drivers and age: are young firms different? Res. Policy 43 (9), 1544–1556.

Garnsey, E., 1998. A theory of the early growth of the firm. Ind. Corp. Change 7 (3), 523–556.

Geroski, P.A., 2000. The growth of firms in theory and in practice. In: Foss, Nicolai, Mahnke, Volker (Eds.), Competence, Governance and Entrepreneurship. Oxford University Press, Oxford, UK, pp. 168–186.

Goedhuys, M., Sleuwaegen, L., 2009. High-growth entrepreneurial firms in Africa: a quantile regression approach. Small Bus. Econ. 34 (1), 31–51.

Haltiwanger, J., Jarmin, R.S., Miranda, J., 2013. Who creates jobs? Small vs large vs young. Rev. Econ. Stat. 95 (2), 347–361.

Hansen, M.T., 1999. The search–transfer problem: the role of weak ties in sharing knowledge across organizational subunits. Admin. Sci. Q. 44 (1), 82–111.

Harrison, R., Jaumandreu, J., Mairesse, J., Peters, B., 2014. Does innovation stimulate employment? A firm level analysis using comparable micro-data from four European countries. Int. J. Ind. Organ. 35, 29–43.
Headd, B., Kirchhoff, B., 2009. The growth, decline and survival of small businesses: an exploratory study of life cycles. J. Small Bus. Manage. 47 (4), 531–550.
Helfat, C.E., Peteraf, M.A., 2003. The dynamic resource-based view: capability lifecycles. Strategic Manage. J. 24, 997–1010.
Herriott, S.R., Levinthal, D., March, J.G., 1984. Learning from experience in organizations. Am. Econ. Rev. 75, 298–302.
Hölzl, W., 2009. Is the R&D behaviour of fast growing SMEs different? Evidence from CIS III data for 16 countries. Small Bus. Econ. 33 (1), 59–75.
Huergo, E., Jaumandreu, J., 2004a. Firms' age, process innovation and productivity growth. Int. J. Ind. Organ. 22, 541–559.
Huergo, E., Jaumandreu, J., 2004b. How does probability of innovation change with firm age? Small Bus. Econ. 22, 193–207.
Hyytinen, A., Maliranta, M., 2013. Firm lifecycles and evolution of industry productivity. Res. Policy 42 (5), 1080–1098.
Jensen, J.B., McGuckin, R.H., Stiroh, K.J., 2001. The impact of vintage and survival on productivity: evidence from cohorts of US manufacturing plants. Rev. Econ. Stat. 83 (2), 323–332.
Kaiser, U., 2009. Patents and profit rates. Econ. Lett. 104 (2), 79–80.
Katila, R., Ahuja, G., 2002. Something old something new: a longitudinal study of search behavior and new product introduction. Acad. Manage. J. 45 (6), 1183–1194.
Koenker, R., 2004. Quantile regression for longitudinal data. J. Multivariate Anal. 91, 74–89.
Koenker, R., Bassett, G., 1978. Regression quantiles. Econometrica 46 (1), 33–50.
Lawless, M., 2014. Age or size? Contributions to job creation. Small Bus. Econ. 42, 815–830.
Levitt, B., March, J., 1988. Organizational learning. Annu. Rev. Sociol. 14, 319–340.
Love, J.H., Roper, S., Du, J., 2009. Innovation, ownership and profitability. Int. J. Ind. Organ. 27 (3), 424–434.
Majumdar, S.K., 1997. The impact of size and age on firm-level performance: some evidence from India. Rev. Ind. Organ. 12, 231–241.
Mata, J., Woerter, M., 2013. Risky innovation: the impact of internal and external R&D strategies upon the distribution of returns. Res. Policy 42, 495–501.
Mazzucato, M., Parris, S., 2015. High-growth firms in changing competitive environments: the US pharmaceutical industry (1963 to 2002). Small Bus. Econ. 44, 145–170.
Miller, C.C., Washburn, N.T., Glick, W.H., 2013. The myth of firm performance. Organ. Sci. 24 (3), 948–964.
Nichols, A., 2007. Causal inference with observational data. Stata J. 7 (4), 507–541.
Nunes, P.M., Serrasqueiro, Z., Leitao, J., 2012. Is there a linear relationship between R&D intensity and growth? Empirical evidence of non-high-tech vs. high-tech SMEs. Res. Policy 41, 36–53.
Pellegrino, G., Piva, M., Vivarelli, M., 2012. Young firms and innovation: a microeconometric analysis. Struct. Change Econ. Dynam. 23, 329–340.
Reinganum, J.F., 1983. Uncertain Innovation and the Persistence of Monopoly. Am. Econ. Rev. 73 (4), 741–748.
Schneider, C., Veugelers, R., 2010. On young highly innovative companies: why they matter and how (not) to policy support them. Ind. Corp. Change 19 (4), 969–1007.
Segarra, A., Teruel, M., 2011. Productivity and R&D sources: evidence for Catalan firms. Econ. Innov. New Technol. 20 (8), 727–748.
Segarra, A., Teruel, M., 2014. High-growth firms and innovation: an empirical analysis for Spanish firms. Small Bus. Econ. 43 (4), 805–821.
Sivadas, E., Dwyer, R.F., 2000. An examination of organizational factors influencing new product development in internal and alliance-based processes. J. Mark. 64 (1), 31–49.
Sorensen, J.B., Stuart, T.E., 2000. Aging, obsolescence, and organizational innovation. Admin. Sci. Q. 45, 81–112.
Taymaz, E., 2005. Are small firms really less productive? Small Bus. Econ. 25, 429–445.
Tornqvist, L., Vartia, P., Vartia, Y.O., 1985. How should relative changes be measured? Am. Statistician 39 (1), 43–46.
Tripsas, M., Gavetti, G., 2000. Capabilities, cognition, and inertia: evidence from digital imaging. Strategic Manage. J. 21 (10–11), 1147–1161.
Veugelers, R., Cincera, M., 2010. BPB Europe's missing yollies. In: Bruegel Policy Brief 2010/06.
Vivarelli, M., Evangelista, R., Pianta, M., 1996. Innovation and employment in Italian manufacturing firms. Res. Policy 25, 1013–1026.
Winter, S.G., 2003. Understanding dynamic capabilities. Strategic Manage. J. 24, 991–995.