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

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ABSTRACT:

This paper explores the relationship between firm growth, innovation and firm age. We hypothesize that young firms undertake riskier innovation activities and are more oriented towards employment growth than towards harvesting returns in the form of sales growth. Using an extensive sample of Community Innovation Survey for the period 2004-2010, we apply quantile regressions and a Heckman sample selection technique to study the impact of R&D activities on firm growth according to firm age. Our results show that R&D intensity is positively associated with firm growth. However, for young firms R&D shows an increasing influence across the quantiles, while for old firms R&D shows a stable or perhaps decreasing effect over the quantiles. Firm age shows a significant negative impact among young firms, while for the sample of old firms the impact of firm age becomes non-significant. Our Heckman estimations show the evolution of the impact of the R&D on firm growth confirming a significant impact on sales and productivity growth, while the impact is negligible for employment growth.

Keywords: firm age, firm growth, innovation, quantile regression

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1. Introduction

Since the works of Nelson (1959), Arrow (1962) and Griliches (1979) an increasing number of analyses have revealed the links between innovation and growth. Few would disagree that innovation is a major driver of economic growth. At the aggregate level, innovation promotes firm competitiveness, generates knowledge spillovers and increases industrial dynamics. At the firm level, an increasing number of empirical studies have analyzed which firm characteristics increase the likelihood to innovate and enhance productivity (Hall et al., 2010, for an extensive survey). However, despite the rapid development of Schumpeterian growth models over the last two decades, our understanding about the relationship between innovation and firm evolution remains incomplete.

The economic literature has devoted increasing attention to heterogeneous innovation performance. However, much discourse in the empirical and theoretical literature only considers the distinction between entrants and incumbents. This lack in the empirical literature is surprising, because according to the Schumpeterian framework, firm age plays a crucial role in a firm's innovation capacity. In the Schumpeterian theory, the level of novelty and imitation of innovations tends to change over the life course.

Furthermore, the empirical evidence is not conclusive. On the one hand, entrants may engage in more radical innovations, improve productivity and engage in more competitive pressure in markets, resulting in the replacement of incumbents. On the other hand, recent empirical evidence by Bartelsman and Doms (2000) and Foster et al. (2002) suggests that incumbents' productivity growth plays a major role in industry productivity growth.

There are some arguments that may explain the scarcity of studies on innovation performance over a firm's life course. First, in the predominant theory age plays a secondary role. Second, only a small number of datasets offer information related to innovation performance and firm age[1]. These limitations cause dramatic effects in a field where time is crucial to take decisions in order to compete and survive.

Innovation can be expected to undergo qualitative transformations within an aging firm. A widely-held view is that "[e]ntrants will come with new products and/or new processes" (Beath, 2002, p233). New firms are assumed to enter with recent capital vintages (Salter, 1960), which can help them achieve higher productivity levels. Empirical evidence, however, suggests that entrepreneurial new/small firms have lower productivity than incumbents, and that they are not more innovative

[1] In particular, the main database used for the empirical studies on innovation at firm level has been the Community Innovation Survey (CIS) coordinated and promoted by OECD that generally does not offer information on firm age.

(see e.g. the surveys by van Praag and Versloot, 2007, and Nightingale and Coad, 2013). Recently, scholars have started to distinguish between small firms and new firms, observing that the contribution of new firms to economic growth is larger than the contribution of small firms (Haltiwanger et al., 2010). In particular, new large firms make a huge impact on the economy in terms of job creation.

Unfortunately, the relationship between innovation and firm age remains under-researched, however. This is unfortunate given the policy interest in the matter - it was recently shown that Europe has fewer young large leading innovators (or 'yollies') than the US (although to a large extent this is due to 'structural' differences in sectoral specializations (Moncada-Paterno-Castello et al, 2010; Veugelers and Cincera, 2010), and that European policy-makers should seek to increase the number of young large leading innovators (Veugelers and Cincera, 2010). One of the major difficulties faced by young European firms is barriers to post-entry growth (Bartelsman et al., 2005).

In this paper, we therefore seek to provide new evidence on the relationship between innovation and firm age, also considering the effects of innovation on firm size and growth (conditional on age). As a measure of innovation, we focus on R&D expenditure. We consider two different groups of firms: those up to 15 years and those with more than 30 years. We assume firms' innovation processes have a dynamic dimension where firms learn during their life course. As firms get older, they gain experience and become more routinized.

We analyze panel data on Spanish innovative firms between 2004 and 2010. 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 results show that R&D effort has a positive impact on firm growth. However, the impact increases over the quantiles of the growth rates distribution of young firms, which is consistent with the idea that R&D of young firms is riskier – in some cases yielding high returns, while in other cases there may be no significant benefits. The effects for old firms are more constant across the quantiles however – with the benefits from R&D being more predictable and stable.

The structure of the paper is as follows. Section 2 outlines the theoretical and empirical literature related to firm age and innovation. Section 3 presents our hypotheses related to the impact of R&D investment according to the firm life cycle. 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 the final section presents the concluding remarks.

2. Firm age and innovation: a review of the literature

2.1 Theoretical literature

2.1.1 Firm life course

The economic literature has developed various theoretical models which describe Schumpeterian processes. One class of those models focuses on the learning process.

On the one hand, in the passive learning model (Jovanovic, 1982) a firm enters a market without knowing its own potential profitability. Only after entry does the firm begin to learn about its own profitability. Each period, firms update their knowledge and decide to expand, contract, or to exit. One of the main implications of this model is that smaller and younger firms should have higher and more variable growth rates.

On the other hand, in the active learning model (Ericson and Pakes, 1995) a firm explores its economic environment actively and invests to enhance its profitability. Its potential and actual profitability changes over time in response to the stochastic outcomes of the firm's own investment, and other competitors in the same market.

In both models the cohorts of entrants are highly heterogeneous: each entrant starts with a different initial size reflecting differences in their own perceived ability. New firms face high barriers to survive (in particular during the first five years) and grow. Although both models are very popular, they present some shortcomings. One limitation is related to innovation activity. These models are not able to capture the types of innovation introduced by entrants and incumbents. A second limitation is that these models do not provide a complete explanation about the simultaneity effect between a firm's learning process and the innovation effort.

We consider that the learning process is crucial for innovation activity and firm performance. In this line, Calantone et al. (2002, p515) state that learning orientation is "an important antecedent of firm innovativeness, which in turn influences firm performance". Furthermore, the impact of internal and external R&D may be different depending on the firm life course: young firms must make a larger R&D effort in order to survive, and internal R&D investment may be crucial for their performance. The main assumption is that successful innovation increases firm competitiveness, which in turn, leads to above-average profits, growth, and further innovation. Therefore, successful innovation by young firms could lead to sustainable competitiveness, whereas low or failed innovation may mean early failure and bankruptcy.

2.1.2 Firm age and innovation strategies

With respect to a firm's early years, empirical investigations into industrial dynamics and the innovation process have found two main results. First, entrants explore the value of new ideas (Audretsch, 1995) which leads to a disruptive effect on the market by introducing new innovations. However, entrants operate in circumstances of high uncertainty, they do not have an established revenue base, and so they might be better able to refocus their sales on new innovative products and services. Second, young firms might over-estimate their capacity to innovate and so their attempts at innovation might be less profitable. Therefore, they are not able to introduce these differences in order to survive in the market.

As a consequence, innovation performance changes along the firm's life course. During the first years, new and small firms need to incorporate disruptive innovation to overcome their high hazard rates. Later survivors enter in a growth path and adopt different innovation strategies.

Furthermore, Abernathy and Clark (1985) and Tushman and Anderson (1986) examine the link between firm type (typically, incumbent versus entrant) and the nature of an innovation (e.g., incremental versus radical). This line of research suggests that incumbent firms may or may not be better at innovating than entrants, depending on the nature of the innovation process. Incumbents may be at an advantage in doing incremental innovations, but might be worse when the new technology requires a significant departure from their core capabilities. For instance, Henderson and Clark (1990) show that architectural innovations tend to destroy the existing knowledge embedded in the structure and systems of established firms. Thus, in this type of innovation, incumbents may actually prove less innovative than entrants. Furthermore, Criscuolo et al. (2012, p321) explain that established firms are more vulnerable to structural inertia, and are less able to adapt their existing 'ways of doing things' in dynamic contexts.

Additionally, Akcigit and Kerr (2010) highlight the heterogeneous performance of incumbents and entrants. Incumbents tend to develop exploitation R&D and applied incremental innovation, while the younger firms enter with new technologies and applied exploratory R&D – like radical innovation. Firms can increase their quality continuously by undertaking incremental R&D in order to grow and increase their productivity. Hence, this evidence is in line with Schumpeterian creative destruction where potential entrants undertake radical R&D in order to replace the mature firms, and incumbents tend to undertake incremental R&D (Klette and Kortum, 2004; Acemoglu and Cao, 2010).

The innovation process requires making sizeable investments in R&D projects and taking substantial risks. It also involves learning from mistakes and failures that are an unavoidable part of the innovation process. Therefore, the knowledge that is gained even from failures can be applied to improve other products. However, only firms with sufficient accumulated profits may be able to survive when one innovative project fails. Empirical evidence shows that old firms are, on average, larger and possess a larger accumulated stock of profits (Coad et al., 2013). Hence, old firms may be more prepared to face up to innovation failures.

2.2 Positive or negative impact of firm age on innovation? – A review of the empirical literature

The empirical literature has found both negative and positive effects of firm age on innovation. Empirical works have highlighted the existence of organization inertia which constrains the firm's ability to change, as well as core organizational functions such as goals, technology, or marketing. For instance, Majumdar (1997) noted that older firms are liable to experience some form of inertia, which may hinder the learning effect. Sorensen and Stuart (2000) identify two effects of age on innovation – learning effects and obsolescence effects. Learning effects 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. Obsolescence then becomes an issue, as the directions of search activities upon which mature firms have embarked are not well suited to the contemporaneous technological landscape. Sorensen and Stuart present evidence supporting both of these contrasting effects in their analysis of semiconductor and biotechnology firms. Relatedly, 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.

Huergo and Jaumandreu (2004a, 2004b) and Huergo (2006) found a negative impact of age on the probability to innovate, which shows the youngest cohorts are, conditional on the peculiarities of their activity and size, prone to innovate more than the oldest ones. However, young firms appear to be under-represented in their data, which might be a source of selection bias. (Note that this problem also affects most other work on innovative activity undertaken by young firms.)

BarNir et al. (2003) found differences in the strategy related to digitization. In fact, established firms digitize activities associated with marketing, administration and communication. However, digitization and innovation efforts are stronger for new versus established firms.

While some studies (surveyed above) have focused on how the nature of 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.

Pellegrino et al. (2012) investigate the difference between young innovative companies (YICs) and their older counterparts using Italian CIS data. They 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.

One area in which our understanding of the moderating role of age on innovative activity and post-innovation performance is lacking, concerns whether the innovative activity of young firms is riskier or more radical than that undertaken by mature firms. 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." By analyzing the distribution of the returns to innovative activity for young and mature firms, we are in a position to assess these differences in the radicalness of innovation.

To sum up, previous empirical evidence shows that new firms typically need time to accommodate to the situation within which they operate. 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, 2004b; 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. However, the productivity growth of new firms may not be especially rapid or smooth, because they must entail costs of experimentation, they must train new employees, and experience many other setbacks in the struggle to establish themselves. Older firms, in contrast, can be expected to be better at steadily improving their productivity, because they implement process innovations, they engage in more incremental innovations, they exploit (rather than explore) and because they seek to harvest previous investments. Hence, productivity growth rates are expected to be negatively correlated with firm age and, as a consequence, the innovative effort will be higher when firms are young (Coad et al., 2013).

However, there is also evidence on the positive impact of firm age on the innovative process. New firms face up to difficulties associated with lack of market recognition and economies of scale and lack of alliances with partners. While over time firms are able to strengthen their available resources, managerial knowledge and the ability to handle uncertainty (Herriott et al., 1984; Levitt and March, 1988). Also they have much more reputation and market position which facilitate relationships and contacts. There is evidence on the positive effect of firm age on the likelihood of superior organizational (Argote, 1999), new product development (Hansen, 1999; Sivadas and Dwyer, 2000) and innovative outcomes (Tripsas and Gavetti, 2000).

3. Hypotheses

On the basis of our theoretical discussion we now derive some hypotheses related to the effect of R&D investments on firm growth, and the role of firm age.

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

For young firms, R&D may either have large positive returns (if successful) or negative returns (if unsuccessful). For old firms, R&D is not purely exploratory but they try to better exploit their existing routines and capabilities. For old firms, the outcome of R&D is more predictable and will have moderate positive returns across the distribution. Akcigit and Kerr (2010) provide empirical evidence from the US Census of Manufacturers that large firms engage more in incremental R&D, while small firms perform radical R&D – and we expect that a similar distinction can be made between old and young firms. Consequently, the distribution of effects of R&D on firm performance differs according to firm age.

> **Hypothesis 1a:** for young firms, R&D has a large positive effect at the upper quantiles of the distribution of performance (measured in terms of growth of employment, sales and productivity)
> **Hypothesis 1b:** for young firms, R&D has a negative effect at the lower quantiles of the distribution of performance (measured in terms of growth of employment, sales and productivity)
> **Hypothesis 1c:** for old firms, R&D has a positive effect on performance across the distribution (where performance is measured in terms of growth of employment, sales and productivity)

A firm's strategies vary across its life course. A young firm will seek to build capabilities (e.g. by investing in human resources) that can be a source of lasting competitive advantage. In general, young firms suffer from diseconomies of scale (because they operate at a size below the minimum efficient scale (MES), and seek an extensive growth performance based on growth of the number of employees, while old firms will avoid the challenges of taking on new employees (which involve internalizing and adapting to new resource configurations) and instead will prioritize an intensive growth strategy based on sales growth. Young firms can also be expected to experience rapid productivity growth as they gain experience in their industries. In contrast, older firms will seek to harvest past investments and convert its resources into superior financial returns (that is, seeking to improve productivity and sales). Coad et al. (2013) find that the growth of young firms puts more emphasis on employment growth, while older firms are better able to turn sales growth into growth of profits. Hence, our hypotheses are the following,

Hypothesis 2: When the firm is young, R&D investment is associated with employment growth, while when firms are mature R&D investment is associated with sales growth.

> **Hypothesis 2a:** for young firms, R&D will have a stronger effect on employment growth than for sales growth
> **Hypothesis 2b:** for old firms, R&D will have a stronger effect on the growth of sales than for employment growth.

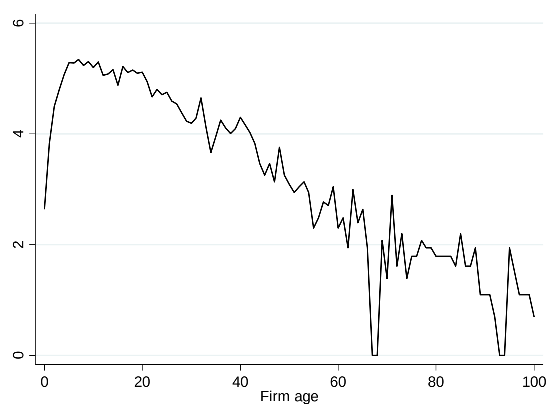
Note, however, that we do not make predictions for differences in innovation success between young and old firms concerning productivity growth. We consider this variable to be more complex. Young firms can be expected to increase productivity because they start from a low productivity level when they enter. Older firms can be expected to increase productivity, because they implement process innovations, incremental innovations, they exploit (rather than explore) and because they seek to harvest previous investments. As such, we expect both young and old firms to increase productivity.

4. Database

This study uses the Technological Innovation Panel (PITEC - Panel Innovación Tecnológica) between 2004 and 2010. The main advantage of PITEC data is that contains detailed information from CIS data related to the innovation behavior and firm characteristics. Furthermore, the data provides the possibility to study the innovation behavior from a dynamic approach. Hence, PITEC overcomes the main drawback of the CIS data given that we may analyze the relationship between firm age, innovation and performance.

The selection of the final database has been the following. First, we exclude firms with 3 or less years of observation[2]. Second, we also exclude firms which are mergers, acquisitions and firms with a sudden increase of sales or employment (maximum 250%).

Figure 1. Firm age distribution (2005)



With respect to representativeness, Figure 1 presents the age distribution for our whole sample and for innovative firms (after data cleaning). Previous work on the age distribution of firms suggests that the firm age distribution of the population of firms is approximately exponential (Coad, 2010). Therefore, 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 a positive skewness.

Age is defined in terms of years since the creation of the business. The mode is equal to 5-7 years and the average firm age is equal to 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, Fig A1). Therefore, we will have to be cautious in interpreting the results for the age group of less than ten years. Unlike some previous work, we do not want to ignore or trivialize this problem, but face up to it and mention it as a priority for future work. However, we acknowledge that we must probably wait for the 'next generation' of innovation datasets.

[2] 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.

With respect to the evolution of the distribution of sales, sales per employee[3] and employees (see Figure A-1 in Annex 1), in line with Cabral and Mata (2003) the density function is skewed towards the right. Furthermore, the skewness diminishes when considering older firms.

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*		*Empl*	
< 10 years	5,088	2,525	24.1	15.5	155,918	151,983	89	69
10 to 19 years	5,371	3,256	39.7	24.0	186,237	158,764	142	108
20 to 29 years	3,555	2,066	27.0	17.9	199,096	180,637	119	95
30 or more	5,376	2,571	128	101	242,861	224,890	421	342
	Firm age		*GrSales*		*GrProd*		*GrEmpl*	
< 10 years	7.32	8.28	8.91	-2.00	5.87	4.00	6.36	-1.66
10 to 19 years	16.34	16.50	1.81	-3.43	2.28	0.47	1.28	-1.34
20 to 29 years	25.70	26.06	-0.09	-4.75	0.24	-0.58	0.79	-2.30
30 or more	50.80	53.85	-1.60	-3.19	0.04	-0.68	-1.01	-1.30

Source: own elaboration
* *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.*

We can see a positive evolution of the variables over time. 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. As has been pointed out in Coad et al. (2013), the evolution of distributions reveals three patterns. First, young firms initially perform worst than older firms. Second, young firms are subject to a higher pressure to survive. Third, market pressure leads to firms to increase their profitability and size in order to survive.

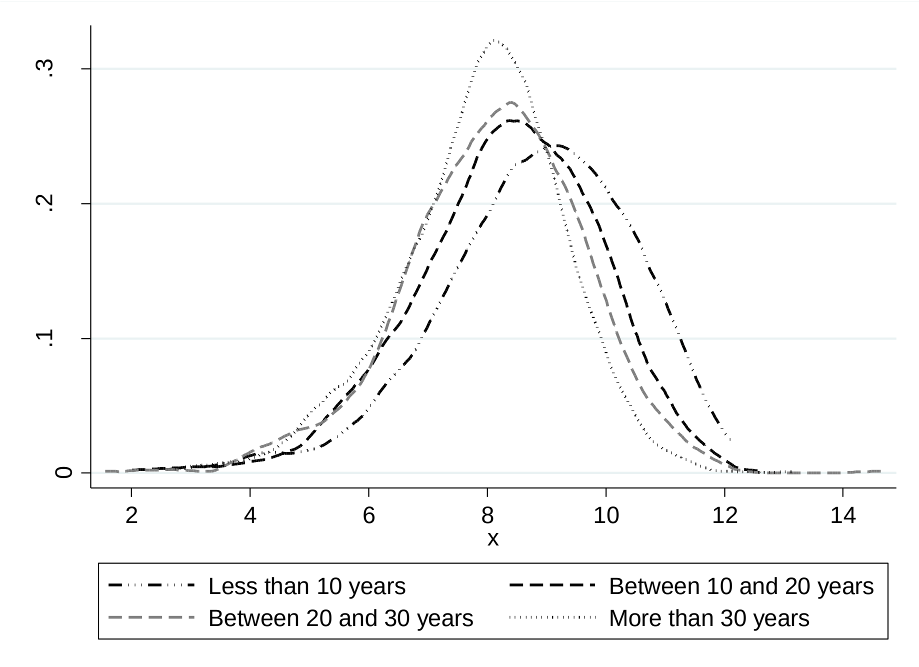
We consider innovative firms as those firms that make an effort to invest in R&D, regardless whether it is internal R&D or external R&D. In that sense, Table 1 shows the main descriptive statistics. We may highlight the following features. First, we observe that 65% of the total number of observations belong to firms that have invested in R&D. Second, the average firm age for our categories (firms with less than 10 years, those between 10 and 19 years, between 20 and 29 years, and firms with 30 or more years) does not show significant differences depending on whether the firms are investing in R&D or not. Third, with respect to the growth rates, there appears a decreasing relationship between firm age and growth rates. Therefore, the older the firm age group, the lower is the growth rate. Finally, there are significant differences between the growth rates of firms investing in R&D and those that they do not invest, regardless the growth variable.

One crucial variable affecting firm performance is the R&D effort. Figure 2 shows the kernel density for our four age groups. As we can see, the distribution of the R&D effort tends to evolve towards the left when firms get older. Our evidence shows that young innovative firms make a larger effort than older firms. On the

[3] As an indicator of productivity, we calculate the ratio of sales per employee for each firm-year observation, which corresponds to "labour revenue productivity" (Bloom et al 2010 p619).

one hand, this may confirm our theoretical framework where young firms make a larger effort in order to differentiate their products and survive in the market. On the other hand, older firms invest a relatively lower amount of resources in R&D activities, perhaps because they are engaged in R&D activities to exploit scale economies.

Figure 2. Kernel density of the ln(R&D investment per employee) in 2006.



In further analysis (Figure A2), we observe that firm growth dispersion decreases among the group of older firms[4]. There are two reasons why young firms may present a higher dispersion. First, young firms may tend to apply radical innovation, with high originality and risk exposition, while mature firms tend to adopt existing knowledge to develop incremental innovation, with less risk. Second, entrants start with less market knowledge and, hence, they may suffer a higher risk on the market.

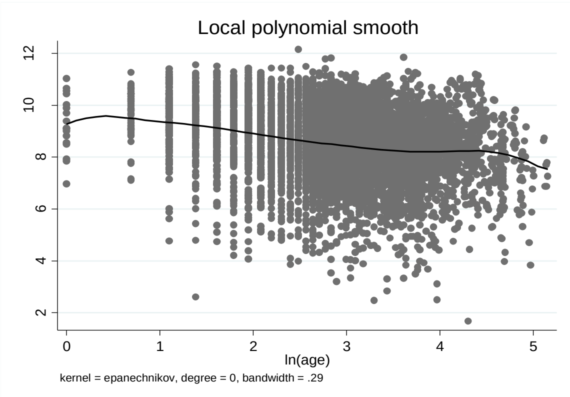
Our main results for the full sample may be complemented by an analysis disaggregated by age groups. Given that our results for the age-class between 4 and 10 years may suffer from being not representative of all young firms, we advise caution in interpreting the results for the firms. In spite of the fact that a high number of studies analyse the heterogeneity of innovation intensity and its relationship to the firm size distribution (e.g., Acs and Audretsch 1987, 1988, Kortum and Lerner 2000), the works that emphasize the impact of firm age across the distribution are scarce.

Similarly, we may suspect that the R&D investment effort differs according to firm age. We used kernel-weighted local polynomial smoothing techniques to

[4] In this line, Figures A-2 show 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).

obtain non-parametric estimates of the dependence of innovation on age. Figure 3 shows the graphical result. As we can see, there is a decreasing impact of firm age on the R&D investment per employee. Hence, we may expect that the impact of R&D will differ according to different group classifications, because each age group is investing a different amount of R&D.

Figure 3. **Local polynomial smooth estimation (2005).**
ln(R&D investment per employee) with respect to ln(age)



5. Econometric methodology

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

$$\Delta \ln Sales_{i,t} = \alpha_{10} + \alpha_{11} \ln Sales_{i,t-1} + \alpha_{12} \Delta \ln Lab_{i,t} + \alpha_{13} \Delta \ln K_{i,t} + \alpha_{14} \ln RDintensity_{i,t-1} + \ldots$$
$$\ldots + \alpha_{15} RDint_{i,t-1} + \alpha_{16} RDext_{i,t-1} + \alpha_{17} \ln Age_{i,t-1} + \alpha_{18} Coop_i + \varepsilon_{1it} \quad [1]$$

$$\Delta \ln SalesLab_{i,t} = \alpha_{20} + \alpha_{21} \ln SalesLab_{i,t-1} + \alpha_{22} \Delta \ln Lab_{i,t} + \alpha_{23} \Delta \ln K_{i,t} + \alpha_{24} \ln RDintensity_{i,t-1} + \ldots$$
$$\ldots + \alpha_{25} RDint_{i,t-1} + \alpha_{26} RDext_{i,t-1} + \alpha_{27} \ln Age_{i,t-1} + \alpha_{28} Coop_i + \varepsilon_{2it} \quad [2]$$

$$\Delta \ln Lab_{i,t} = \alpha_{30} + \alpha_{31} Lab_{i,t-1} + \alpha_{32} \Delta \ln K_{i,t} + \alpha_{33} \ln RDintensity_{i,t-1} + \ldots$$
$$\ldots + \alpha_{34} RDint_{i,t-1} + \alpha_{35} RDext_{i,t-1} + \alpha_{36} \ln Age_{i,t-1} + \alpha_{37} Coop_i + \varepsilon_{3it} \quad [3]$$

where α_i are the coefficients and ε_{it} is the usual error term for firm *i* at time *t*. The dependent variable is the annual log-difference. 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 ($\Delta lnLab$), productivity growth (measured as sales per employee, also known as 'labour revenue productivity', $\Delta lnSalesLab$), and sales growth ($\Delta lnSales$).

As explanatory variables, we include the following variables:

1. R&D intensity measured as the natural log R&D investment per sales (*lnRDintensity*).
2. To investigate the process of convergence on firm performance, we include as explanatory variables the lagged value of the dependent variable in levels (*lnSales*, *lnSalesLab* and *lnLab*),
3. In order to control for the input factors we include in all equations the natural log of capital growth (Δ*lnK*) and in equations [1] and [2] the natural log of employees growth (Δ*lnLab*).
4. We also include two dummy variables which control for the type of R&D (internal R&D –*RDint*- and external R&D –*RDext*-).
5. We include a dummy variable for R&D cooperation activity (*Coop*).
6. We include also the natural log of firm age measured as the difference between the current year and the year the firm registers to start business (*lnAge*).
7. Finally, we also control for sectoral differences and macroeconomic effects by including sectoral and year dummies.

In order to estimate the impact of the R&D effort on firm performance, we apply a quantile regression procedure (Koenker and Bassett, 1978). Quantile regression has been frequently applied to analyse issues related to the distribution of returns to innovation (Coad and Rao, 2006; Coad and Rao, 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 Wörter, 2013; Bartelsman et al., 2013). 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 several other reasons. First, the standard least-squares assumption of normally distributed errors does not hold for our data because innovation expenditure and innovation intensity display a skewed distribution. Second, while conventional regressions focus on the average firm, quantile regression can describe the complete conditional distribution of the dependent variable. Third, quantile regression is robust to outliers on the dependent variable, which is important in our present context, because growth rate distributions are well known to be heavy-tailed. As we have seen in Figure A2, younger firms show a higher variability in growth, both when growth is measured in terms of employment as when sales growth is measured. Hence, quantile regressions may be a good technique to capture the heterogeneity among firms.

The quantile regression estimator was designed for the analysis of cross-sections. Although theoretical developments in applying quantile regression to panel contexts have recently emerged (Koenker, 2004; Galvao, 2011) they are yet to be implemented in standard statistical software packages (such as Stata). Furthermore, the interpretation of panel quantile regression results is quite different from the interpretation of cross-sectional quantile regression results, because of the panel within-transformation. We therefore perform quantile regressions on pooled cross-sections of annual growth rates, and so we apply standard quantile regression instead of attempting the panel variant. One potential problem with pooling cross-sections in this way is that the observations for the same firms for different years may not be statistically independent. We believe this problem to be relatively unimportant, however, considering that the firm growth literature emphasizes that growth is largely random, there is little correlation in growth rates over time, and that there is more variation in growth rates within firms than across firms over time (Geroski and Gugler, 2004), all of which suggest that time-invariant firm-specific fixed effects do not help determine firm growth rates (Coad, 2009). Nevertheless, to investigate the role of problems associated with pooling cross-sections, we repeated our analysis on subsamples of individual cross-sections (corresponding to growth rates of different firms over the same time period) and obtained similar results. We also repeated the analysis with a cross-section of firms where growth was measured over the period 2007-2010. Although focusing on this longer cross-section considerably reduces the number of observations, nevertheless 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.)

The nature of innovation at the firm level is likely to be affected by endogeneity between innovative activities and firm growth. In others words, firms that enjoy growth (or even firms that anticipate that they will grow) may be able to commit resources to subsequent innovation activity (Coad and Rao, 2010). Using a firm-level data from the CIS II (1993–95) Cainelli et al. (2006) show for service firms that innovation is positively affected by past economic performance and that innovation activities have a positive impact on both growth and productivity. Finally, we report bootstrapped standard errors to ensure precision in our inference.

6. Results

6.1 Innovation and firm performance: Quantile estimations

Tables 2, 3 and 4 present five regression quantile results for the quantiles $\theta = 0.10$, 0.25, 0.50, 0.75 and 0.90 in addition to OLS estimation. Quantile regression coefficients can be interpreted as the marginal change in y at the θ*th* 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 impact of the factor across the conditional distribution of the dependent variable (firm growth). As we will see, we obtain different results depending on the quantiles. We consider young firms as those with less than 15 years old, while old firms correspond to those firms with more than 30 years. The classification responds to the necessity to create two different groups with a similar number of firms. Our results are the following.

First, the lagged absolute value of the dependant variable (*lnSales*, *lnSalesLab* and *lnLab*) generally shows a negative and significant impact on firm growth. Furthermore, we must highlight that the negative impact is higher for the upper quantiles for employment growth. Our results are in line with previous evidence on firm growth, since Gibrat's Law is not accomplished, although the result is stronger for upper quantiles.

Second, when considering the growth of the input factors, we observe significant and expected signs. On the one hand, an increase in employment ($\Delta lnLab$) presents a positive impact on the sales growth, while the impact becomes negative when considering labour productivity. We must highlight that the impact decreases for the upper quantiles of the oldest firms, while the impact among the younger firms remain similar across quantiles. With respect to growth of capital (ΔlnK), the impact is positive regardless the variable. However, the parameter shows a decreasing pattern across quantiles, and becomes non-significant in some cases. In particular, the impact is non-significant for the upper quantiles of the sales growth among young firms, and we find a similar pattern for the upper quantiles of the labour productivity.

Table 2.
OLS and quantile regression estimates for sales growth (ΔlnSales) of young firms and old firms.

	Young firms (<15 years)						Old firms (>30 years)					
	OLS	**Q0.10**	**Q0.25**	**Q0.5**	**Q0.75**	**Q0.9**	**OLS**	**Q0.10**	**Q0.25**	**Q0.5**	**Q0.75**	**Q0.9**
$lnSales_{t-1}$	-0.0149***	0.0046	-0.0017	-0.0048**	-0.0185***	-0.0250***	-0.0062**	0.0032	0.0027	-0.0029**	-0.0036**	-0.0091**
	(0.0037)	(0.0086)	(0.0020)	(0.0021)	(0.0033)	(0.0054)	(0.0029)	(0.0032)	(0.0019)	(0.0012)	(0.0015)	(0.0036)
ΔlnLab	0.489***	0.460***	0.435***	0.504***	0.468***	0.475***	0.475***	0.517***	0.470***	0.468***	0.428***	0.385***
	(0.0305)	(0.0449)	(0.0250)	(0.0244)	(0.0191)	(0.0348)	(0.0417)	(0.0646)	(0.0453)	(0.0297)	(0.0296)	(0.0439)
ΔlnK	0.0092***	0.0118**	0.0100***	0.0045**	0.0047	0.0061	0.0148***	0.0100**	0.0074***	0.0058***	0.0060***	0.0056**
	(0.0028)	(0.0058)	(0.0034)	(0.0019)	(0.0033)	(0.0038)	(0.0056)	(0.0044)	(0.0018)	(0.0016)	(0.0019)	(0.0026)
lnRDintensity	0.0123***	0.0048	0.0051**	0.0085***	0.0124***	0.0198***	0.0153***	0.0202***	0.0073***	0.0027	0.0079***	0.0076**
	(0.0036)	(0.0079)	(0.0024)	(0.0024)	(0.0024)	(0.00347)	(0.0037)	(0.0039)	(0.0027)	(0.0016)	(0.0022)	(0.0031)
RDint	-0.0001	-8.45e-05	2.03e-05	-6.39e-05	-0.0002	-3.68e-05	2.27e-05	8.33e-05	0.0001*	9.96e-05	1.16e-05	2.18e-05
	(0.0001)	(0.0002)	(0.0001)	(0.0001)	(9.97e-05)	(0.0002)	(0.0001)	(0.0002)	(7.04e-05)	(6.85e-05)	(6.91e-05)	(0.0001)
RDext	-1.79e-05	7.48e-05	-0.0002	-8.00e-05	7.59e-05	-0.00015	0.0005***	0.0004	0.0003***	0.0003***	0.0003*	0.0003*
	(0.0002)	(0.0003)	(0.0002)	(0.0001)	(0.0002)	(0.0003)	(0.0001)	(0.0003)	(0.0001)	(0.0001)	(0.0001)	(0.0002)
lnAge	-0.0263***	0.0009	-0.0071	-0.0161**	-0.0485***	-0.106***	0.0028	0.0076	0.0042	0.0043	0.0048	0.0180
	(0.0090)	(0.0129)	(0.0070)	(0.0067)	(0.0066)	(0.0156)	(0.0143)	(0.0108)	(0.0102)	(0.0064)	(0.0055)	(0.0171)
Coop	0.0101	0.0063	0.0032	0.0022	0.0055	-0.0097	-0.0032	-0.0016	-0.0029	0.0050	-8.29e-05	0.0064
	(0.0090)	(0.0134)	(0.0096)	(0.0077)	(0.0070)	(0.0139)	(0.0073)	(0.0073)	(0.0065)	(0.0040)	(0.0052)	(0.0117)
Constant	0.670***	-0.261	-0.152	0.121	0.638***	0.899***	0.159**	0.0676	0.0162	0.0549	0.0621	0.0638
	(0.113)	(0.232)	(0.101)	(0.150)	(0.169)	(0.151)	(0.0776)	(0.116)	(0.118)	(0.232)	(0.249)	(0.186)
R-squared	0.204	0.1506	0.1342	0.1110	0.1411	0.1700	0.201	0.2255	0.2159	0.1545	0.1239	0.1290
Observations				4,797						5,793		

Estimations control for time and sector dummies.
Robust standard errors in parentheses.
*** p<0.01, ** p<0.05, * p<0.1

Table 3.
OLS and quantile regression estimates for productivity growth (ΔlnSalesLab) of young firms and old firms.

	Young firms (<15 years)						Old firms (>30 years)					
	OLS	**Q0.10**	**Q0.25**	**Q0.5**	**Q0.75**	**Q0.9**	**OLS**	**Q0.10**	**Q0.25**	**Q0.5**	**Q0.75**	**Q0.9**
lnSalesLab	-0.0718***	-0.0719***	-0.0458***	-0.0445***	-0.0497***	-0.0664***	-0.0480***	-0.0453***	-0.0236***	-0.0136***	-0.0154***	-0.0173**
	(0.0077)	(0.0142)	(0.0060)	(0.0060)	(0.0056)	(0.0122)	(0.0107)	(0.0119)	(0.0043)	(0.0042)	(0.0047)	(0.0072)
ΔlnLab	-0.488***	-0.505***	-0.542***	-0.489***	-0.512***	-0.518***	-0.495***	-0.472***	-0.495***	-0.522***	-0.553***	-0.631***
	(0.0301)	(0.0341)	(0.0344)	(0.0272)	(0.0309)	(0.0497)	(0.0411)	(0.0560)	(0.0337)	(0.0230)	(0.0324)	(0.0435)
ΔlnK	0.0082***	0.0115**	0.0094***	0.0049***	0.0042*	0.0056	0.0147***	0.0089*	0.0075***	0.0061***	0.0049***	0.0048
	(0.0027)	(0.0051)	(0.0025)	(0.0018)	(0.0024)	(0.0039)	(0.0056)	(0.0050)	(0.0024)	(0.0013)	(0.0016)	(0.0038)
lnRDintensity	0.0027	-0.0104**	-0.0035	0.0038	0.0121***	0.0179***	0.0099***	0.0096**	0.0022	0.0028**	0.0069***	0.0077***
	(0.0032)	(0.0047)	(0.0026)	(0.0030)	(0.0030)	(0.0046)	(0.0037)	(0.0041)	(0.0017)	(0.0011)	(0.0018)	(0.0024)
RDint	-5.58e-05	9.10e-06	-3.99e-06	-7.55e-05	-0.0001	0.0003	-6.66e-07	-1.54e-05	7.94e-05	7.30e-05	-6.39e-06	2.58e-06
	(0.0001)	(0.0002)	(0.000125)	(8.35e-05)	(0.0001)	(0.0003)	(0.0001)	(0.0001)	(8.62e-05)	(7.20e-05)	(8.43e-05)	(0.0001)
RDext	0.0002	0.0001	-7.43e-05	0.0001	0.0001	0.0002	0.0004***	0.0002	0.0003***	0.0003***	0.0003*	0.0003
	(0.0002)	(0.0003)	(0.0002)	(0.0001)	(0.0002)	(0.0004)	(0.0001)	(0.0002)	(0.0001)	(0.0001)	(0.0001)	(0.0002)
lnAge	-0.0289***	0.0143	-0.0071	-0.0210***	-0.0502***	-0.114***	0.0021	-0.0056	0.0086	0.0056	0.0066	0.0123
	(0.0088)	(0.0116)	(0.0081)	(0.0053)	(0.0082)	(0.0206)	(0.0146)	(0.0161)	(0.0083)	(0.0056)	(0.0082)	(0.0130)
Coop	0.0087	0.0120	0.0076	0.0007	0.0012	-0.0156	-0.0019	0.0057	0.0028	0.0033	-0.0012	0.0043
	(0.0087)	(0.0155)	(0.0073)	(0.0046)	(0.0075)	(0.0135)	(0.0074)	(0.0097)	(0.0037)	(0.0034)	(0.0055)	(0.0077)
Constant	1.310***	0.582***	0.344***	0.581***	0.950***	1.301***	0.596***	0.432	0.105	0.0110	0.0434	0.0374
	(0.132)	(0.212)	(0.123)	(0.195)	(0.196)	(0.248)	(0.119)	(0.337)	(0.375)	(0.161)	(0.296)	(0.247)
R-squared	0.171	0.1288	0.1252	0.0961	0.1128	0.1430	0.165	0.1635	0.1553	0.1223	0.1225	0.1410
Observations	4,797						5,793					

Estimations control for time and sector dummies.
Robust standard errors in parentheses.
*** p<0.01, ** p<0.05, * p<0.1

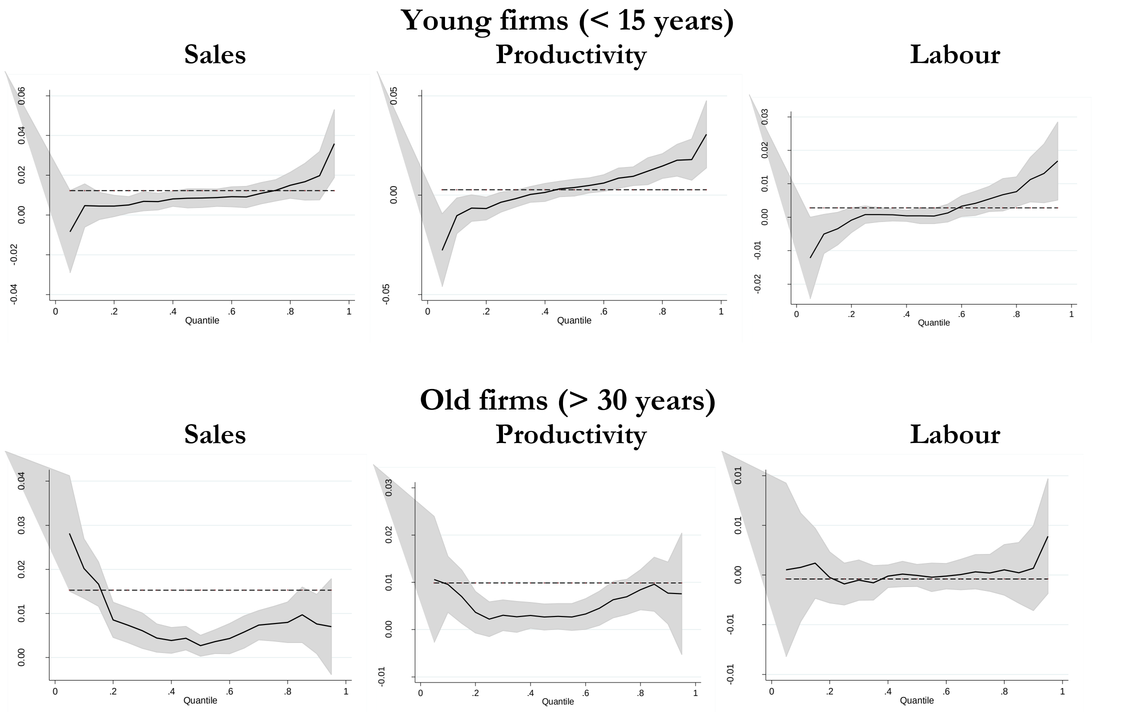
Table 4.
OLS and quantile regression estimates for labour growth (ΔlnLab) of young firms and old firms.

	Young firms (<15 years)						Old firms (>30 years)					
	OLS	**Q0.10**	**Q0.25**	**Q0.5**	**Q0.75**	**Q0.9**	**OLS**	**Q0.10**	**Q0.25**	**Q0.5**	**Q0.75**	**Q0.9**
lnLab	-0.0194***	0.0012	-0.0055***	-0.0124***	-0.0246***	-0.0334***	-0.0074***	0.0014	-0.0004	-0.0030***	-0.0050***	-0.0119***
	(0.0028)	(0.0045)	(0.0020)	(0.0019)	(0.0023)	(0.0047)	(0.0018)	(0.0038)	(0.0015)	(0.0010)	(0.0012)	(0.0029)
ΔlnK	0.0091***	0.0089***	0.0064***	0.0050***	0.0084***	0.0123***	0.0057***	0.0039**	0.0048***	0.0030***	0.0031***	0.0033
	(0.0019)	(0.0024)	(0.0014)	(0.0011)	(0.0015)	(0.0029)	(0.0014)	(0.0019)	(0.0012)	(0.0009)	(0.0008)	(0.0020)
lnRDintensity	0.0028	-0.0050	0.0008	0.0004	0.0067***	0.0131***	-0.0004	0.0008	-0.0009	-4.86e-05	0.0002	0.0007
	(0.0020)	(0.0031)	(0.0019)	(0.0012)	(0.0017)	(0.0033)	(0.0012)	(0.0020)	(0.0017)	(0.0006)	(0.0007)	(0.0018)
RDint	7.23e-06	0.0001	9.87e-05	3.89e-05	1.39e-06	-0.0001	-2.38e-06	2.99e-05	-2.66e-05	-3.20e-05	2.40e-05	4.05e-05
	(9.19e-05)	(0.0001)	(9.07e-05)	(5.47e-05)	(0.0001)	(0.0002)	(5.14e-05)	(8.53e-05)	(4.49e-05)	(2.84e-05)	(4.17e-05)	(7.10e-05)
RDext	9.25e-05	0.0001	0.0001	5.98e-05	0.0001	-0.0002	0.0002***	0.0003***	0.0001**	7.94e-05	7.08e-05	9.79e-05
	(0.0001)	(0.0002)	(0.0001)	(8.25e-05)	(0.0002)	(0.0003)	(7.18e-05)	(0.0001)	(4.97e-05)	(5.60e-05)	(4.63e-05)	(6.63e-05)
lnAge	-0.0234***	-0.0128	-0.0087*	-0.0169***	-0.0308***	-0.0587***	0.0008	-0.0054	-4.30e-05	0.00165	-0.0015	0.0030
	(0.0064)	(0.0079)	(0.0046)	(0.0037)	(0.0076)	(0.0173)	(0.0057)	(0.0122)	(0.0052)	(0.0023)	(0.0036)	(0.0079)
Coop	0.0159***	-0.0031	0.0049	0.0089***	0.0161**	0.0183	0.0105***	0.0202***	0.0079***	0.0031**	0.0010	0.0009
	(0.0060)	(0.0105)	(0.0049)	(0.0031)	(0.0065)	(0.0123)	(0.0033)	(0.0061)	(0.0027)	(0.0015)	(0.0023)	(0.0053)
Constant	0.203***	-0.0582	-0.0222	0.135***	0.271**	0.395***	0.0963***	0.118	0.0896	0.0879	0.101	0.102
	(0.0349)	(0.0847)	(0.0666)	(0.0503)	(0.111)	(0.131)	(0.0241)	(0.224)	(0.0895)	(0.112)	(0.0803)	(0.152)
R-squared	0.082	0.0473	0.0390	0.0404	0.0845	0.1224	0.073	0.0920	0.0598	0.0343	0.0440	0.0493
Observations	4,797						5,793					

Estimations control for time and sector dummies.
Robust standard errors in parentheses.
*** p<0.01, ** p<0.05, * p<0.1

Third, investment in R&D (*lnRDintensity*) shows in general a positive and significant impact on firm growth regardless the variable. However, we must highlight differences across quantiles. For young firms we observe a significant and increasing impact over the distribution. Hence, young firms with high growth rates are more positively affected by R&D investment in comparison with those firms belonging to lower quantiles. In fact, for growth of labour productivity and employment, we observe a negative impact for the lowest quantiles, which suggests that R&D investment is not always successful (Demirel and Mazzucato, 2012; Nunes et al., 2012). When considering the group of older firms the pattern is positive, but it shows a decreasing pattern across quantiles. Hence, older firms with high growth rates will benefit less from R&D investment in comparison with old firms in the lower quantiles. We must point out that the sign is not significant for old firms' employment growth rates.

Figure 4.
Quantile graphs. Impact of R&D intensity on firm growth for young and old firms.



Coefficients of R&D intensity across quantiles. The respective values are connected by a solid black line along with an estimated 95%-confidence band. The OLS coefficient is a broken horizontal line.

To show the evolution in the marginal effects of innovation sources on firm productivity in greater detail, Figure 4 presents six graphs that describe the elasticity of R&D intensity with respect to our three growth measures. An explanation for the low impact of R&D investment on employment growth may be because successful innovators might improve productivity by reducing their labour input requirements. In general, empirical evidence agrees that product innovations have a positive impact on employment (Bogliacino et al., 2011), while process innovations tend to displace employment (Harrison et al., 2008).

As a consequence, our hypotheses H1a) and H1b) would be accepted. On the one hand, young firms that achieve higher growth rates are positively affected by investment in R&D activities. On the other hand, those firms with low growth rates are negatively affected by R&D investment. Furthermore, hypothesis H1c) may be accepted in part since the pattern for sales growth is decreasing and negative for the upper quantiles, but the behaviour for growth of labour productivity and employment is much flatter.

Fourth, with respect to the incidence of the R&D strategy, we observe that internal R&D (*RDint*) activity does not show a significant impact regardless the dependent variable and the group of firms. However, mature firms that invest in external R&D (*RDext*) show a significant and positive impact on the firm growth regardless the growth measure (cf Mata and Woerter 2013).

Fifth, firm age (*lnAge*) shows a significant impact among young firms with a decreasing pattern. Hence, while firm age exerts a positive impact among young firms in the lower quantiles, the impact becomes negative for those firms at the upper quantiles. The impact is non-significant among old firms.

Finally, the dummy variable indicating those firms that cooperate (*Coop*) presents a non-significant impact with the exception of the impact on employment growth. On the one hand, for young firms the impact becomes significant and positive for the upper quantiles. On the other hand, when considering old firms the impact on employment growth is significant and positive for the lower quartiles, but the parameter decreases and becomes non-significant for the upper quantiles.

6.2 Innovation and firm performance: Heckman selection model

In our previous equations, firm growth depends on R&D, so our results will be observed if the firm decides to invest in R&D. The empirical literature has highlighted that firms that invest in R&D may differ in many ways from those firms that do not invest. Hence, we apply a Heckman equation where our main previous equations [1] – [3]. Now we include a first step which measures the probability that a firm invests in R&D. Our first equation will be:

$$\mathrm{RD}^*_{\mathrm{it}} = \left\{ \begin{array}{l} \beta_0 + \beta_1 \mathrm{lnLab}_{\mathrm{it}} + \beta_2 \mathrm{lnAge}_{\mathrm{it}} + \beta_3 \mathrm{Internationalmarket}_{\mathrm{it}} + \beta_4 \mathrm{Group}_{\mathrm{it}} + \mathrm{u}_{\mathrm{it}} \quad if \quad RD = 1 \\ 0 \quad otherwise \end{array} \right\} \quad [4]$$

RD is a dummy variable that indicates whether a firm invests in R&D. β corresponds to the parameters to be estimated and *u* is the error term. Equation [4] depends on the following explanatory variables:

1. Firm size (*lnLab*): Natural log of the number of employees. We consider that large firms are in a better position to invest in R&D. We expect that large firms will invest more in R&D.
2. Firm age (*lnAge*): Natural log of firm age. We consider young firms will have to invest more frequently in R&D in order to be more competitive with respect to incumbents.
3. International market (*International*): Percentage of exports with respect to total sales. We consider that firms in international markets are engaged in more intense competition; hence, it is likely that they will carry out more innovation projects.
4. Group (*Group*): Dummy variable that takes a value equal to 1 if the firm belongs to a group. We consider a firm belonging to a corporate group will be more likely to engage in R&D compared to an independent firm.
5. Sectoral dummies: Dummy variables for each sector. We consider that firms in some sectors may be more likely to engage in R&D activities due to higher sunk costs or competitiveness levels.
6. Time dummies: Dummy variables for each year. During booms R&D investment might be easier than during recessions.

Our main equations controlling for the sample selection will correct for the fact that we only consider firms that invest in R&D. Hence, we include the correlation coefficient ρ between the error terms (*u*) of equation [4] and the error terms of equations [1] to [3] (ε_1, ε_2, and ε_3). Hence, we will obtain the following equation [5] to [7]:

$$\Delta \ln \mathrm{Sales}_{i,t} = \begin{cases} \alpha_{10} + \alpha_{11} \ln \mathrm{Sales}_{i,t-1} + \alpha_{12} \Delta \ln \mathrm{Lab}_{i,t} + \alpha_{13} \Delta \ln \mathrm{K}_{i,t} + \alpha_{14} \ln \mathrm{RDintensity}_{i,t-1} + \ldots \\ \ldots + \alpha_{15} \mathrm{RDint}_{i,t-1} + \alpha_{16} \mathrm{RDext}_{i,t-1} + \alpha_{17} \ln \mathrm{Age}_{i,t-1} + \alpha_{18} \mathrm{Coop}_{i} + \rho_{1t} + \varepsilon_{1it} \quad if \quad RD = 1 \\ 0 \end{cases} \quad [5]$$

$$\Delta \ln \mathrm{SalesLab}_{i,t} = \begin{cases} \alpha_{20} + \alpha_{21} \ln \mathrm{SalesLab}_{i,t-1} + \alpha_{22} \Delta \ln \mathrm{Lab}_{i,t} + \alpha_{23} \Delta \ln \mathrm{K}_{i,t} + \alpha_{24} \ln \mathrm{RDintensity}_{i,t-1} + \ldots \\ \ldots + \alpha_{25} \mathrm{RDint}_{i,t-1} + \alpha_{26} \mathrm{RDext}_{i,t-1} + \alpha_{27} \ln \mathrm{Age}_{i,t-1} + \alpha_{28} \mathrm{Coop}_{i} + \rho_{1t} + \varepsilon_{1it} \quad if \quad RD = 1 \\ 0 \end{cases} \quad [6]$$

$$\Delta \ln \mathrm{Lab}_{i,t} = \begin{cases} \alpha_{30} + \alpha_{31} \ln \mathrm{Lab}_{i,t-1} + \alpha_{32} \Delta \ln \mathrm{K}_{i,t} + \alpha_{33} \ln \mathrm{RDintensity}_{i,t-1} + \ldots \\ \ldots + \alpha_{34} \mathrm{RDint}_{i,t-1} + \alpha_{35} \mathrm{RDext}_{i,t-1} + \alpha_{36} \ln \mathrm{Age}_{i,t-1} + \alpha_{37} \mathrm{Coop}_{i} + \rho_{3t} + \varepsilon_{3it} \quad if \quad RD = 1 \\ 0 \end{cases} \quad [7]$$

According to our results (Table 5), the parameter ρ is significant and indicates that residuals between the main and the selection equation are significantly correlated.

Hence, our Heckman procedure would help to correct for non-observable characteristics of firms which invest in R&D.

With respect to the selection equation, we observe the following results. First, firm size exerts a significant and positive impact on R&D activity, but the impact is larger for old firms. Second, firm age shows a negative impact on the probability of investing in R&D activities, but the impact is more negative for young firms. As a consequence, our results show that large and younger firms will present a larger propensity to invest in R&D. Our results are in line with Moncada-Paterno-Castello et al. (2010) and Veugelers and Cincera (2010). Third, firms competing in international markets show a significant larger propensity to invest in R&D. The impact is larger for old firms in comparison with young firms. Fourth, belonging to a group shows a positive impact on R&D activity. However, the effect is not always significant. In line with Tiwari et al. (2008) and Galia et al. (2012), this evidence indicates that firms may obtain financial support for their R&D activities more easily when they belong inside a group of firms.

With respect to the main equation, as we have seen previously (Tables 2, 3 and 4) the lagged absolute value shows a negative impact on firm growth. However, the impact is larger for young firms than for older firms regardless the variable we consider. The impact related with the growth of input factors (labour and capital) are similar to our previous results based on quantile estimations. However, in comparison with old firms, capital growth shows a slightly larger impact for young firms on sales and productivity growth, while this variable shows a slightly smaller impact for young firms when considering employment growth.

More remarkable is the impact of the R&D intensity. As we have seen previously, R&D shows a positive effect on firm growth; however the impact is larger for young firms when we observe sales and employment growth, while the impact is larger for old firms when we observe labour productivity growth. As we have explained in our hypotheses section, we did not have any expected impact of R&D on labour productivity according with firm age. Our result may be in line with Bartelsman and Doms (2000) and Foster and Krizan (2000) who point out that incumbents' productivity growth plays a major role in industry productivity growth. However, according to our results it is likely that old firms will invest in R&D activities which enhance their productivity, while young firms will try to increase their firm size and market share.

Taking into account our results with respect to our hypotheses, H2a) and H2b) would be partially accepted. Regardless the sample of firms, the R&D intensity shows a larger impact on sales growth than for employment growth. Hence, H2a) would not be accepted while H2b) would be.

Table 5.
Estimations using the Heckman equation.

	Whole database			Less than 15 years			More than 30 years		
	ΔlnSales	**ΔlnSalesLab**	**ΔlnLab**	**ΔlnSales**	**ΔlnSalesLab**	**ΔlnLab**	**ΔlnSales**	**ΔlnSalesLab**	**ΔlnLab**
lnSales	-0.0278***			-0.0304***			-0.0223***		
	(0.0018)			(0.0034)			(0.0027)		
lnSalesLab		-0.0595***			-0.0821***			-0.0533***	
		(0.0032)			(0.0064)			(0.0053)	
lnLab			-0.0199***			-0.0297***			-0.0153***
			(0.0014)			(0.0032)			(0.0018)
ΔlnLab	0.451***	-0.519***		0.455***	-0.509***		0.448***	-0.512***	
	(0.0129)	(0.0130)		(0.0225)	(0.0223)		(0.0246)	(0.0249)	
ΔlnK	0.0112***	0.0112***	0.0059***	0.0078***	0.0072***	0.0075***	0.0096***	0.0099***	0.0056***
	(0.0013)	(0.0013)	(0.0008)	(0.0027)	(0.0026)	(0.0019)	(0.00214)	(0.0021)	(0.0012)
lnRDintensity	0.0114***	0.0096***	0.0037***	0.0146***	0.0074**	0.0037*	0.0100***	0.0084***	-0.0008
	(0.0016)	(0.0016)	(0.0010)	(0.0035)	(0.0034)	(0.0022)	(0.0026)	(0.0026)	(0.0014)
RDint	-1.41e-05	-3.69e-06	1.70e-05	0.0001	0.0001	-4.77e-05	1.50e-05	1.30e-05	-4.80e-06
	(8.20e-05)	(8.15e-05)	(5.26e-05)	(0.0002)	(0.0002)	(0.0001)	(0.000121)	(0.0001)	(6.85e-05)
RDext	0.0001	0.0002	0.0001	0.0002	0.0004	-7.83e-06	0.00037**	0.0003*	0.0002**
	(0.0001)	(0.0001)	(7.48e-05)	(0.0003)	(0.0003)	(0.0002)	(0.0002)	(0.0002)	(9.85e-05)
lnAge	-0.0083**	-0.0176***	-0.0154***	-0.0081	-0.0142	-0.0125*	0.0259**	0.0145	0.0023
	(0.0033)	(0.0032)	(0.0019)	(0.0102)	(0.0100)	(0.00655)	(0.0112)	(0.0109)	(0.0058)
Coop	0.0035	-0.0023	0.0138***	-0.0025	-0.0081	0.0141**	-0.0056	-0.0108*	0.0102***
	(0.0042)	(0.0042)	(0.0027)	(0.0092)	(0.0090)	(0.0064)	(0.0065)	(0.0064)	(0.0036)
Constant	0.832***	1.056***	0.321***	0.872***	1.277***	0.345***	0.654***	0.892***	0.210***
	(0.0325)	(0.0386)	(0.0156)	(0.0678)	(0.0770)	(0.0331)	(0.0692)	(0.0790)	(0.0338)
	Selection equation (Probability of investing in R&D)								
lnLab	0.134***	0.0916***	0.159***	0.0797***	0.0393***	0.0991***	0.171***	0.132***	0.198***
	(0.0073)	(0.0071)	(0.0080)	(0.0136)	(0.0132)	(0.0153)	(0.0134)	(0.0130)	(0.0145)
lnAge	-0.0613***	-0.0393***	-0.0676***	-0.243***	-0.231***	-0.232***	-0.0588	-0.0365	-0.0572
	(0.0125)	(0.0125)	(0.0130)	(0.0404)	(0.0405)	(0.0415)	(0.0445)	(0.0445)	(0.0456)
International	0.519***	0.549***	0.615***	0.487***	0.520***	0.550***	0.657***	0.692***	0.792***
	(0.0179)	(0.0182)	(0.0206)	(0.0317)	(0.0321)	(0.0368)	(0.0374)	(0.0381)	(0.0439)
Group	0.0842***	0.107***	0.0571***	0.0465	0.0789**	0.0428	0.0595**	0.0836***	0.0142
	(0.0170)	(0.0173)	(0.0189)	(0.0326)	(0.0332)	(0.0364)	(0.0294)	(0.0301)	(0.0331)
Constant	-1.365***	-1.226***	-1.501***	-0.484***	-0.336**	-0.612***	-1.949***	-1.825***	-2.144***
	(0.0645)	(0.0643)	(0.0662)	(0.132)	(0.131)	(0.136)	(0.211)	(0.210)	(0.216)
Rho	-1.124***	-1.082***	-0.677***	-1.082***	-1.044***	-0.637***	-1.156***	-1.108***	-0.666***
	(0.0202)	(0.0209)	(0.0304)	(0.0406)	(0.0415)	(0.0622)	(0.0348)	(0.0362)	(0.0540)
		26,190			3,503			8,394	

Estimations control for time and sector dummies
Robust standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

With respect to R&D strategies, we observe similar results: internal R&D shows a non-significant impact while external R&D shows a significant and positive impact on firm growth for old firms. Firm age shows a negative impact for the whole database; however when we split up our sample according to firm age, we observe that for young firms the impact is negative and significant only for the employment growth, while for old firms the sign is significant and positive for sales growth. Hence, it seems that old firms may be able to exploit their experience to obtain larger market sales, while young firms will increase the number of employees during the first years.

Finally, cooperation activity shows a positive impact on employment growth among young firms, while among old firms the impact is positive for employment growth and negative for productivity growth.

In order to capture the evolution of the impact of R&D intensity (*lnRDintensity*) on firm growth according to age, Figure A-3 in Annex 1 shows the evolution of the parameter when we include firms with one more year, and when estimating the values for each year. We may observe that when including older firms, the impact of R&D on firm growth decreases. Furthermore, the impact on sales and labour productivity tend to converge. If we take into account the estimation for each year, we observe that the impact of R&D does not show such a clear pattern. We must point out that missing estimations are due to lack of convergence of the model. Hence, we may suspect that the R&D evolution is erratic when considered year-by-year, while the pattern may smooth when considering the accumulated firms' behaviour.

7. Conclusions

The main objective of this article was to analyse the relationship between firm age, innovation 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 impact of R&D effort on firm growth according to firm age.

Our results show that R&D intensity positively affects firm growth regardless the firm age. However, some important differences appear. First, for young firms the impact increases across quantiles, while old firms show a negative or stable impact across quantiles. This suggests that innovation undertaken by young firms is uncertain and unevenly distributed, while the innovation efforts of older firms are more predictable. Second, when applying Heckman procedure we observe similar results (although these results focus on average effects). In fact, the impact of R&D on sales is larger than for labour productivity and employees. However, the impact on sales and employees is larger for young firms, while the impact on labour productivity is larger for old firms. In part, this effect may be due to the fact that young firms try to grow to reach minimum efficient scale, while old firms invest in R&D activities in order to increase their efficiency and exploit their economies of scale. Furthermore, firm size shows a significant negative effect on firm growth (regardless the variable), but the impact is larger among young firms. With respect to firm age, this variable exerts a significant negative effect for young firms, while old firms do not show a significant impact. Finally, when considering the probability to invest in R&D, our results are in line with previous evidence: larger firms which compete in international markets and belonging to a group of firms will have a larger probability to invest in R&D activities. However, firm age shows a significant negative effect for young firms.

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 (cf our Heckman estimates in Table 5). 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.

Why do 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, it could be because performance indicators for young firms are more volatile (e.g. if young firms have a more dispersed growth rates distribution). Future work could fruitfully try to distinguish between these reasons.

Finally, we contribute to the literature by analysing firm performance according to firm age. However, we are aware that further work 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.

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Appendix

Figure A-1

Kernel density of the ln(sales), ln(sales per employee) and ln(employees) in 2005.

Kernel density of ln(Sales) Kernel density of ln(Sales per employee) Kernel density of ln(employees)

Figure A-2

Kernel density of the ln(sales), ln(sales per employee) and ln(employees) in 2006 for firms investing in R&D.

Kernel density of growth ln(Sales) Kernel density of ln(Sales per employee) Kernel density of ln(employees)

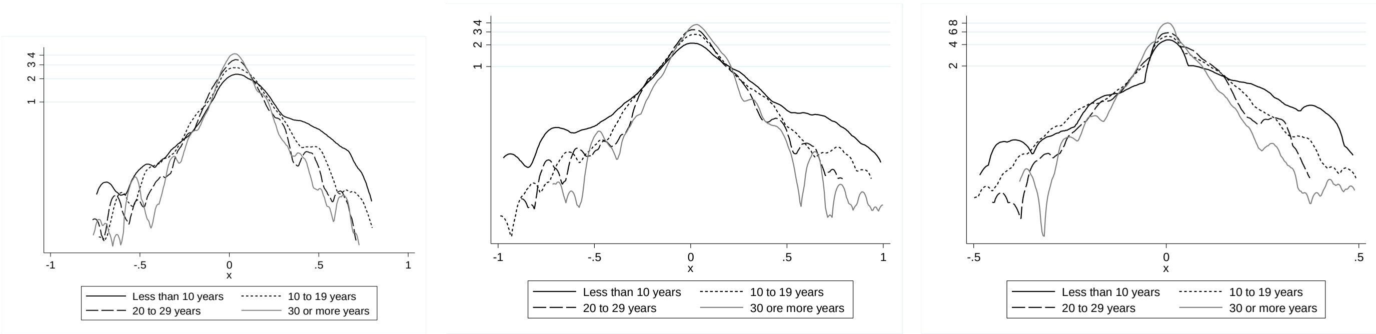
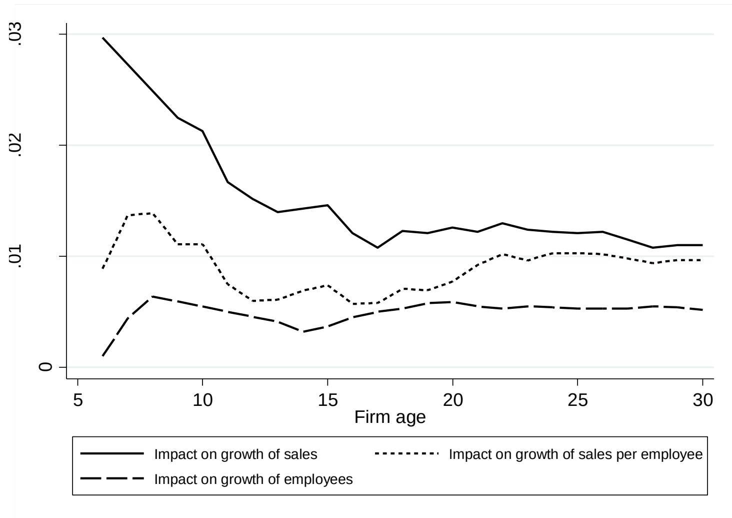


Figure A-3. Evolution of the elasticity of R&D intensity on firm growth. Heckman estimations.

Cumulative age



Each age