Persistence of innovation and patterns of firm growth*

Dario Guarascio° and Federico Tamagni†°

°Institute of Economics – Scuola Superiore Sant'Anna, Pisa, Italy

Abstract

In this work we test if persistent innovators, defined according to different innovation activities (R&D, product and process innovation, patenting) grow more than other firms, and if innovation persistence can contribute to explain the so far little evidence in favor of persistence in growth itself. We exploit a somewhat uniquely long-in-time dataset tracing a representative sample of Spanish manufacturing firms over the period 1990-2012. This allows to overcome the difficulties in the definition of persistent innovators traditionally based on innovation surveys. Our findings, against the expectations, support that persistent innovators do not generally outperform the other firms. First, they do not grow more, and actually we find that, despite some variation across innovation persistence indicators, they even grow less than other firms in the top-quantiles of the growth rates distribution, that is among high-growth firms. Further, persistent innovators do not show higher growth persistence than other firms, in none of the quantiles of the growth rates distribution, independently from the innovation persistence indicator considered.

JEL codes: D22, O30, C21

Keywords: firm growth, innovation persistence, product and process innovation, R&D, patents, quantile regressions

*This paper is produced as part of the project "ISIGrowth: Innovation-fuelled, Sustainable, Inclusive Growth" that has received funding from the European Union's Horizon 2020 research and innovation programme, grant agreement No. 649186 – ISIGrowth.

† *Corresponding author*: Federico Tamagni, Scuola Superiore San'Anna, Pisa, Italy. Postal address: c/o Institute of Economics, Scuola Superiore Sant'Anna, Piazza Martiri 33, 56127, Pisa, Italy, *E-mail* f.tamagni@sssup.it, *Tel* +39-050-883343.

1 Introduction

The relationship between innovation and firm growth has attracted and continues to attract the attention of both theorists and applied economists. Such interest is motivated by the widespread opinion that innovation is one of the main drivers of corporate growth. In policy terms, this emphasis contributed to the diffusion of tools aimed at facilitating adoption and development of innovation in firms.

As it often happens, however, common wisdom and theoretical predictions do not find robust and unequivocal counterparts in empirical terms. This is true also for the innovation-growth nexus, as indeed empirical studies provide heterogeneous results regarding the statistical significance, the magnitude and the direction of such relation. The contrasting findings are rooted in the complex nature of both firm growth and innovation dynamics. On the one hand, the determinants of firm growth have proven to be hardly identifiable from an empirical standpoint. On the other, innovation patterns are characterized by intrinsic uncertainty and multidimensionality, in turn reflected in the heterogeneous effect that different proxies of innovation activity – distinguishing inputs vs. outputs, or internal vs. external sources of innovation – may have on firm growth. The empirical research exploring the innovation-growth nexus at the firm level found hard to document a strong positive relationship between the two dimensions of firm dynamics. This is especially the case when looking at the effect of innovation on growth of the "average firm". Indeed, despite the initial supporting evidence gathered in classical studies (Mansfield, 1962; Mowery, 1983), more recent ones have repeatedly documented the lack of any relation (Geroski et al., 1997; Geroski, 2002; Bottazzi et al., 2001). A number of subsequent studies, thus, shifted the attention to the variation of the innovation-growth relationship along the quantiles of the growth rates distribution, motivated by the overwhelming evidence that firm growth is characterized by fat-tails (Bottazzi and Secchi, 2006). This literature tends to show that innovation is indeed beneficial for growth, but that this is the case only for the small set of high-growth firms in the top quantiles of the growth rates distribution (Freel, 2000; Coad and Rao, 2008; Hölzl, 2009; Falk, 2012; Nunes et al., 2012; Colombelli et al., 2013). However, the results may be sensitive to the specific proxy of innovation used (Bianchini et al., 2016). As Audretsch et al. (2014) recently put it, *"...despite the emergence of a vast empirical literature on whether innovative firms grow more quickly in terms of sales and employees, a number of crucial questions and answers remain..."*

In this work we seek to add new evidence to the debate by studying the links between firm growth and *persistence* of innovation.

The existence and the determinants of persistence in innovation are the subject of a large literature. As emphasized in the recent review by Le Bas and Scellato (2014), the different analyses reflect the explanation of innovation persistence advanced in the literature. The Schumpeterian interpretation points to the market structure and, in particular, to the role of incumbent firms in monopolistic and oligopolistic markets. These firms tend to innovate persistently to defend their market shares from the threat of new entrants. Other studies rely upon the knowledge accumulation hypothesis (Geroski et al., 1997; Duguet and Monjon, 2004; Bas and Latham, 2009), according to which innovation persistence is due to learning-by-doing effects, to the cumulative and incremental nature of innovation as well as to the emergence of dynamic capabilities. The success-breed-success hypothesis is that firms succeeding in innovating will be those able to reach above-the-average profits, and thus to accumulate the resources needed to innovate further (Cefis and Ciccarelli, 2005). Lastly, a further explanation of innovation persistence refers to the sunk costs of performing R&D activities, implying that firms get stuck into a certain technological regime and, thus, develop technological competitiveness strategies based on past knowledge accumulation and internal capabilities (Antonelli et al., 2013). Whatever the theoretical approach, the empirical evidence is that the degree of innovation persistence differs in place, time, and industry, as well as according to the specific type of innovation activity considered, distinguishing persistence in terms of - for instance - R&D activities, product or process innovation, or others dimensions of the innovation process.

What is, then, the relationship between innovation persistence and other dimensions of firm structure and performance? No matter the preferred explanation for the emergence and nature of innovation persistence, all theoretical frameworks implicitly or explicitly predict persistent innovators to be more capable than other firms in seizing larger economic benefits from innovation in itself. Yet, the links between innovation persistence and firm growth remains largely underexplored. To our knowledge, this topic is tacked only in two articles. Demirel and Mazzucato (2012), restricting the analysis to the pharmaceutical sector, show that persistence in patenting works as a condition to be fulfilled in order for R&D to impact positively on firm growth. Deschryvere (2014) exploits a panel of Finnish firms to show that only SMEs that continuously innovate – in terms of both product and process innovation – are characterized by a positive association between R&D and sales growth.

We contribute to this limited empirical literature in several ways. First, we do not only investigate whether persistent innovators grow more than other firms, as already did in the scant literature cited above, but we also explore whether innovation persistence affects persistence of growth itself. To the best of our knowledge, while a relatively large literature explores persistence of growth itself, with mixed results, there is no previous attempt to test whether persistent innovators exhibit higher persistence than other firms in their growth trajectories. Second, by exploiting a panel of Spanish firms spanning the period 1990-2012, we can follow the same firms over a considerably long period of time, and thus overcome some difficulties in measuring innovation persistence. Studies on innovation persistence, indeed, in most of the cases, distinguish between persistent and occasional innovators based on innovation surveys (such as the CIS or others). But the rotating nature of the samples and the release in waves usually covering 2 or 3 years, without information on firms' behaviour between two consecutive survey waves, affect the accuracy and reliability of the identification of innovation persistence (Raymond et al., 2010). In particular, we design a strategy to identify persistent innovators that, albeit simple, allows to soften the potential endogeneity between innovation performance and firm growth. Third, again exploiting the rich data available, we can perform separate analysis for different innovation proxies (R&D, product and process innovation, and patenting), thus capturing whether the effects of innovation persistence on growth patterns vary depending on the type and nature of innovation activity. Lastly, and in tune with the recent developments in the literature on firm growth and innovation, we apply quantile regression techniques to explore the possibly heterogeneous effect of innovation persistence across firms positioned in the different quantiles of the growth rates distribution. In doing so, we estimate standard conditional quantile regressions, with a first-step Probit correction for endogenous classification of firms into the group of persistent innovators.

2 Empirical framework and research questions

Our empirical strategy is strictly intertwined with the availability of data that allows to follow a representative sample of firms over a relatively long period of time. In this Section we present the definition of persistent innovators and the empirical framework which we apply to contrast the growth patterns of persistent innovators vis a vis other firms. Details on the dataset, the main variables and the characteristics of persistent innovators are presented later in Section 3.

2.1 Defining innovation persistence

A number of different approaches has been followed to measure persistence in the innovative activity of firms. In many studies, the main concern lies in understanding if persistence itself exists. Different notions of persistence are used (in terms of, e.g., length of innovation spells, degree of autocorrelation or properties of transition matrices) corresponding to different empirical models. These studies have gathered useful evidence on the "average" degree of persistence in a given sample of firms, often also investigating the determinants of persistence, but they do not provide an operational definition of persistent innovators, however.

A smaller number of studies starts from an a-priori definition of persistent innovators. The common approach is to identify as persistent innovators those firms that repeatedly perform a given innovation activity over time. However, this conceptually simple notion of persistence is confronted with a number of practical issues, related to the characteristics of the data typically available. Innovation surveys, such as the CIS, which have been increasingly exploited as the basis for studying innovation persistence (see Raymond et al., 2010; Deschryvere, 2014), are usually organized in waves released every 2 or 3 years, covering in most cases rotating samples of firms across the different waves. Although it may seem natural to define as persistent innovators those firms that positively answer to survey questions related to innovation activities over two or more consecutive waves, this approach is doomed to only partially hit the target. It can be applied only to firms appearing in more waves, while we do not know what happens over time to firms that, for whatever reason, are not surveyed in all waves. Moreover, even for those firms tha appear and report to be innovative in some waves, we usually lack information about their innovation behavior in the years between two subsequent surveys, so that we cannot really say with full certainty if they persistently innovate over time.

The availability of longitudinal data allowing to follow the same firms over many years provides, in this respect, a more reliable test bed. Yet, further complications arise even when consistent panel datasets are available. First, the notion of persistence that one can measure quite depends on the length of the time span covered in the available data. In fact, in the existing studies, we observe that more firms are able to persistently innovate over shorter time horizons (Le Bas and Scellato, 2014). Second, from previous studies we also know that different innovation activities are to a different extent likely to be repeatedly undertaken over time. Such heterogeneity is related to the very nature of the different innovation activities, and not necessarily due to a direct decision of the firms to undertake a certain activity only sporadically over time. For instance, R&D represents a "weak" measure of innovative persistence, since some R&D expenditures are very likely to be recorded in many years by firms that do perform some R&D in at least one year. Conversely, filing for patents or introducing new products can be considered as "strong" measures for identification of innovation persistence, due to inherently more complex processes underlying these two innovation outcomes. The existing evidence indeed suggests that the stronger the measure of innovation behavior and the shorter the time period in which a firm innovates (see, again, the review in Le Bas and Scellato, 2014). Finally, a further complication arises when the aim of the analysis is not merely to identify a group of persistent innovators, but rather to link innovation persistence to other firm characteristics and performances, in order to explore either the determinants or the effects of persistence. There is an inherent simultaneity issue to be tackled, since the definition of persistent innovators is likely to both influence and at the same time to be influenced by other firm characteristics. Of course, the shorter in time is the available panel and the more difficult is to break this joint determination. Conversely, with more years available there is more room to break endogeneity, as one can measure innovation persistence and other characteristics, such as growth, in non-overlapping years.

Taking advantage of the data that allow to observe firms over a period of 23 years (1990-2012), we design an empirical strategy that tries and tackles these methodological problems.

As a first step, we divide the sample into two sub-periods: the first ten years (1990-1999) are used to identify the group of persistent innovators, while we use the second half of the sample period (2000-2012) to perform our regression analysis exploring whether the growth trajectories of persistent innovators identified in the first period differ from the growth patterns of the other firms. This implies that the definition of persistent innovators is completely predetermined with respect to the years in which we measure firm growth, considerably reducing simultaneity bias.

Second, to define persistent innovators in the first subperiod, we follow the common approach to count how many times each firm reports to perform a certain innovation activity. Since we work here with yearly data (and not survey waves), many different criteria are in principle available at this step, concerning how many years can be considered enough to qualify a firm as persistently innovative, and whether one should restrict the persistent innovator category to only include firms innovating in consecutive years or to also include firms with year-gaps in between two innovation events. All choices are to some extent arbitrary. Ideally, a seemingly unquestionable definition of persistent innovator would be that of a firm that is always performing a given innovation activity in all the years over the first subperiod. But this does not verify in the data. There is clearly a trade-off between a more stringent and more precise definition including only firms that innovate in most of the available years, and the need to come up with a not too small group of persistent innovators, so to ensure meaningful comparisons with the other firms in the regressions estimated on the second subperiod. Lacking a precise guidance from previous studies, we have experimented with different criteria, and eventually define as persistent innovators those firms performing innovative activities for at least 7 out of 10 years in the period 1990-1999. With this criterion, we surely capture firms innovating not occasionally over the considered period, and substantially limit the possibility of long gaps between two innovation events. The same criterion for the identification of persistent innovators is applied separately to four different innovation indicators recorded in the data for each firm in each year: the amount of R&D expenditures in the year, the number of newly filed patents, and the introduction of both product and process innovation. This allows us to account for the potential heterogeneity emerging when persistence is evaluated according to different innovation dimensions.

2.2 Research questions and econometric strategy

We exploit the classification of firms into persistent innovators vs. other firms described above to investigate two features of the growth dynamics experienced by the two groups of firms over the second part of the available time-span (2000-2012).

First, we ask whether persistent innovators grow more than other firms. We address this question through the following regression equation

$$G_{it} = \beta_0 + \beta_1 \, Pers_i + \beta_2 \, X_{it-1} + u_{it} \tag{1}$$

where the subscript it stands for the firm-year pair running over the years 2000-2012, G_{it} is firm growth, and $Pers_i$ is a dummy assuming value 1 for firms identified as persistent innovators in the years 1990-1999, on the basis of the different innovation indicators. The omission of the t subscript underlines that, given our empirical setting, each firm cannot change "innovation persistence status" in the regression subperiod. The set of firm-level controls X includes a number of standard firm characteristics used in the literature on firm growth. These are age, size, productivity and R&D intensity, all lagged to reduce simultaneity. The coefficient of primary interest is β_1, capturing the "growth premium" for persistent innovators.

The second research question is directed at inquiring if persistence in innovation is associated to persistence of growth itself. In tune with the empirical literature on persistence of firm growth, we model persistence in growth rates as an autoregressive process and, thus, specify the following regression model

$$G_{it} = \alpha_0 + \alpha_1 \, G_{it-1} + \alpha_2 \, Pers_i + \alpha_3 G_{it-1} \times Pers_i + X_{it-1} + u_{it} \; . \tag{2}$$

Here, G, $Pers$, X are defined as in Equation (1) above. We use 1-year lagged growth, G_{it-1}, to capture persistence of growth, and interact the lagged dependent with $Pers_i$ to model the potential additional contribution to growth persistence associated to the status of persistent innovator. Thus, the coefficient α_1 captures the degree of growth autocorrelation among firms that are not classified as persistent innovators, while α_3 is the additional "growth persistence premium" for persistent innovators. The sum $\alpha_1 + \alpha_3$ gives the autocorrelation of growth for persistent innovators.

In agreement with the increasing literature on the links between innovation and firm growth, in estimating both Equation (1) and Equation (2) we complement simple OLS with quantile regressions (QR) techniques to explore the variation of coefficient estimates along the conditional distribution of growth rates. In fact, beyond a general interest into exploring heterogeneities across growing and shrinking firms, previous studies are increasingly recognizing that innovation dynamics are particularly important for high-growth firms in the top quantiles of the growth rates distribution, whereas the "average effect" of innovation is often difficult to uncover. This fact directly relates to the abundant evidence (confirmed also in our data, see below) that firm growth rates are indeed fat-tailed. QR techniques are robust to outliers and non-Gaussian distribution of the error term. We use here standard conditional quantile regression (Koenker and Bassett, 1978).

As discussed, possible joint determination between growth and the persistent innovator dummies is fairly reduced by the overall empirical strategy adopted, since the definition of $Pers$ does not directly exploit data over the years 2000-2012 considered to analyse the dynamics of growth. A risk of bias remains, however, since observed and unobserved firm characteristics that are responsible for the assignment to the groups of persistent innovators in the first period might be correlated with unobserved determinants of growth in the second period. At least to the extent that believes that innovation performance in the very last years of the first sub-periods are driven by forecasts of future growth occurring in the initial years of the second sub-period. We address this issue by means of a two-steps procedure. As a preliminary step, we use the data in the first sub-period 1990-1999 to run a Probit where the innovation persistence dummy $Pers$ (separately for each innovation indicator) is regressed against the same set of firm-level controls included in the main regression models (age, size, R&D intensity and productivity), plus an additional variable given by intangible assets per employee: this is likely correlated with innovation and $Pers$ in the first period, but we do not include it in the regressions run on the second period. Since $Pers$ does not vary over time, these first-step Probit models take as regressors the firm-level time-series average of the included covariates. Then, the firm-specific fitted probabilities (henceforth $P - scores$) obtained from the first-step Probit are subsequently added as an additional regressor in the OLS and QR estimates of Equation (1) and Equation (2) performed on the data over the period 2000-2012, thus cleaning the potentially endogenous dummy $Pers$ from its relationships with first-period values of the controls. [1]

[1] We also experimented with a different first-step Probit where persistent innovator status is regressed against the values of the covariates observed over the estimation time-period 2000-2012. The results of the main estimates presented in the rest of the paper did not change, however. All the results of the different first-step Probit estimates are available upon request.

3 Measuring innovation persistence: data and descriptive analysis

We now present the data and the definition of the main variables, and provide descriptive comparisons between persistent innovators and other firms, as defined through the identification criteria discussed above.

3.1 Data and main variables

The empirical analysis exploits data from the Spanish Survey on Business Strategies (*ESEE - Encuesta Sobre Estrategias Empresariales*), maintained by the SEPI foundation and the Spanish Ministry of Industry. This database provides information on a representative sample of Spanish firms observed over the period from 1990 to 2012. The reference population is composed of firms with 10 or more employees active in manufacturing. The survey since its initial creation in 1990 is run every year, and SEPI implements a number of quality checks to ensure consistency of the panel over time. A relevant characteristic is the high degree of representativeness. The selection of surveyed firms in the initial year was done according to both exhaustiveness and sampling: all firms with more than 200 employees entered the survey together with a stratified sample (via proportional and systematic sampling) of smaller firms employing from 10 to 200 employees, for a total of 2,188 firms included. In subsequent years strong efforts have been done to avoid deterioration of representativeness against the reference population, soliciting firms to keep high response rates, and new firms enter the survey each year to substitute for firms that exit the sample.

About 1,800 firms are surveyed each year using a questionnaire with 107 questions and more than 500 specific fields, mostly oriented toward strategic dimensions of the firms, but also including standard business register information on firms' balance sheets and profit/loss accounts, together with "CIS-type" questions on innovative performance and strategies. As such, and differently from other innovation surveys designed mainly to collect information on firms' innovative activities, the ESEE dataset provides an extremely large and rich set of variables covering firms' structure and performance.[2]

The dependent variable in our analysis is firm growth in terms of sales, which we compute, for each firm i and year t, as the log-difference

$$G_{it} = s_{it} - s_{it-1} \quad , \tag{3}$$

where s_{it} is the log of annual turnover normalized by the (2-digit) sectoral average

$$s_{it} = log(S_{it}) - \frac{1}{N}\sum_{i=1}^{n} log(S_{it}) \ . \tag{4}$$

This definition of G keeps consistency with previous studies investigating fat-tail properties of growth rates. The normalization implicitly removes common trends in sales, such as due to prices or demand cycles, affecting all the firms in the same sector.

We then exploit four variables of the ESEE dataset to build indicators of innovation persistence along different dimensions of the innovative activity of firms. We use total expenses in R&D during the year, and two dummies indicating whether a firm in each year reports to have

[2]For further details on the characteristics of the ESEE dataset, see Jaumandreu and Farinas (1999). An increasing number of works recently exploited the strengths of the ESEE database. Triguero et al. (2014) analyse persistence of innovation activities using discrete-time duration models. Fariñas et al. (2015) study the relationship between productivity and inputs sourcing strategies, while Beneito et al. (2015) explore the relation between competition and firms innovative performance.

Table 1: Persistent innovators in the sample

	Number of firms	Share
R&D persistent	357	11%
Product innovation persistent	100	3%
Process innovation persistent	386	12%
Patenting persistent	35	1%

Notes: Number of persistent innovators by innovation persistence indicator, and the relative percentage over the total number of firms (3193) in the data.

introduced a new product or a new process. The definitions of these variables comply with international standards (according to the Oslo manual). The ESEE also reports information on the number of new patents filed during the year (for patent filed either in Spain or abroad). It is by counting how many times these 4 innovation proxies are non-zero for each firm during the period 1990-1999 that we apply our 7-out-10 years criterion that qualifies a firm as belonging to the group of persistent innovators ($Pers$=1), separately for each innovation indicator.

In choosing the set of firm controls, we had access only to a relatively small subset of the ESEE data, and also needed to cope with the sometimes limited coverage over time of potentially relevant firm-level variables. We can nonetheless cover the set of standard firm characteristics usually employed in firm growth regressions. First, we control for age and size, which are well known important determinants of firm growth. Younger and smaller firms typically grow more, and there is increasing evidence suggesting heterogeneous effects along the growth rates distribution, with high-growth firms being typically smaller and younger. In particular, age can play a relevant mediating role in the relationship between high-growth and innovation (Coad et al., 2016). We measure age from the year of foundation of the firm, reported in the ESEE data, while we consider size in terms of number of employees. Second, we also include a measure of labour productivity, computed as value added per hour worked, on the theoretical grounds that more productive firms are usually expected to grow more (despite most available evidence cast doubts on this prediction, see Bottazzi et al., 2010; Dosi et al., 2015). Further, we also want to control for knowledge and innovation dynamics occurring over the estimation period, since this can easily matter for growth, once again with potentially differentiated impact, especially for high-growth firms. Therefore, we include a measure of R&D intensity, defined as annual R&D expenditures per employee. Finally, we also include a full set of sector and year fixed effects in the OLS estimates, and year dummies only in the QR analysis.[3]

3.2 Identification of persistent innovators

Table 1 reports the number of persistent innovators identified in the data over the first ten years (1990-1999) and still present in the period used for the analysis (2000-2012), distinguishing by innovation indicator. In line with previous studies, the figures highlight that persistent innovators represent a relatively small cluster over the whole set of companies covered in the data. Some heterogeneity emerges across the different innovation proxies. Firms persistently performing R&D during the considered period are 357, corresponding to about the 11% of the total. Persistent product innovators are relatively less frequent, involving the 3% of firms, while firms found to persistently carrying out process innovation are the 12%. Persistence in patenting is an even less widespread, observed only in 1% of the firms. The relatively higher frequency of

[3]In fact, the relatively small number of firms falling into the persistent innovators group (see below) does not allow to identify sector-specific intercepts in the growth quantiles.

Table 2: Correlation between indicators of innovation persistence

	Persistent in R&D	Persistent in Prod. Innov.	Persistent in Proc. Innov.	Persistent in Patenting
Persistent in R&D	1.0			
Persistent in Prod. Innov.	0.42*	1.0		
Persistent in Proc. Innov.	0.34*	0.27*	1.0	
Persistent in Patenting	0.25*	0.22*	0.17*	1.0

Notes: Pairwise correlations. * denotes significance at 1% level.

firms being persistent in performing R&D rather than in performing product innovations or in patenting could be related to the well known uncertainty and complexity of innovation, as not all of the investment in innovation inputs translates in a formalized innovative outcome. On the innovation-output side, on the other hand, the figures tend to confirm the intuition that the introduction of new processes is "easier" than performing the whole steps leading to the actual introduction of new products. The even lower figures for patenting may reflect similar considerations related to the difficulty to come up with an object ready for "the patent race". But they may also reflect other considerations related to patent systems functioning and firm specific preferences for innovation protection strategies.

Table 2 reports the pairwise correlations between the four innovation persistence indicators, as a way to appreciate the different degree of overlapping between the groups. In general, the correlation is not high. The stronger associations are found between persistent product innovators and persistent R&D innovators (0.42), and between the latter and persistence in process innovation (0.34). Other pairs show even smaller correlations. This testifies that the different definitions of persistent innovators indeed identify different groups of firms. That is, it is likely that most firms found to be persistent with respect to one innovation dimension are not necessarily persistent innovators also along another innovation activities. Such heterogeneities confirm the relevance of analyzing the behavior of persistent innovators across different dimensions of innovation.

Notice, lastly, that the persistent innovators that we identify over the initial years 1990-1999, continue to be innovative also over the subsequent estimation period 2000-2012. Indeed, we find that about 70% of them perform some type of innovation for at least 6 years also in the second part of the sample time span, and 50% of them show positive R&D expenses for at least 8 years in the same period.

3.3 Growth and firm characteristics across persistent innovators and other firms

As a preliminary empirical exercise, we explore the 'identity cards' of persistent innovators, providing a descriptive comparison against other firms over the estimation time period 2000-2012.

In Table 3 we report basic descriptive statistics (median and standard deviation) of sales growth and firm controls, pooling all the data over time. Persistent innovators – however defined – do not show strikingly larger median growth, with the exception of persistent patenting firms. Conversely, persistent innovators are larger and older in median than other firms, no matter the innovation persistence indicator considered. A more homogeneous picture emerges concerning productivity, and to some extent also with respect to R&D intensity, although the median is in this case a bit higher for persistent patenters and somewhat smaller for persistent process

Table 3: Descriptive statistics of main variables

		Persistent in R&D	**Persistent in Prod. Innov.**	**Persistent in Proc. Innov.**	**Persistent in Patenting**	**Other Firms**
Sales growth	Median	0.01	0.01	0.01	0.03	0.01
	Std. Dev.	0.33	0.24	0.36	0.18	0.29
Age	Median	43	41	36	43	24
	Std. Dev.	22	22	21	23	21
#Employees	Median	317	267	142	453	35
	Std. Dev.	1263	1631	1257	677	503
Productivity	Median	10.7	10.6	10.6	10.6	10.1
	Std. Dev.	0.6	0.6	0.7	0.5	0.6
R&D intensity	Median	0.006	0.007	0	0.019	0
	Std. Dev.	0.24	0.02	0.24	0.04	0.09

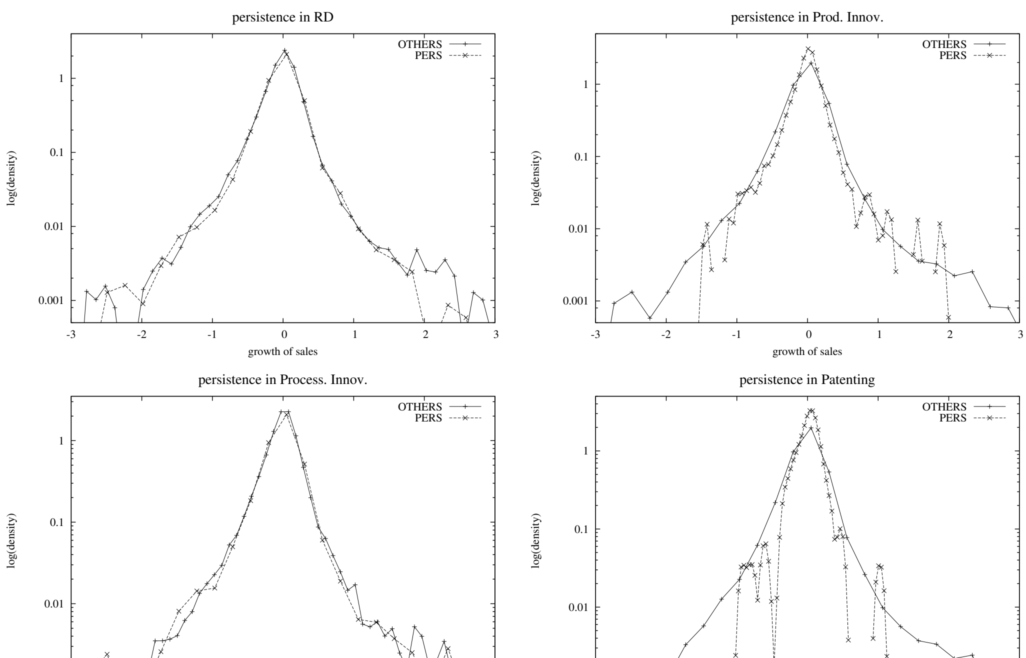

Figure 1: Kernel densities of sales growth, for persistent innovators (PERS) vs. other firms (OTHERS), by different innovation persistence indicators.

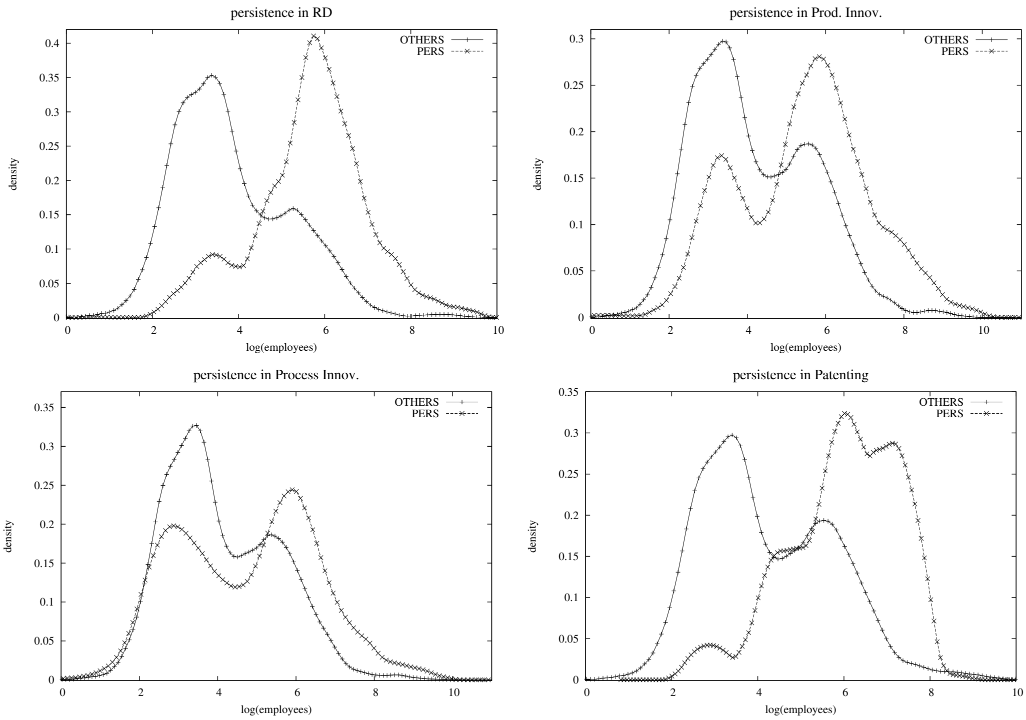

Figure 2: Kernel densities of firm size, as (log) employees, for persistent innovators (PERS) vs. other firms (OTHERS), by different innovation persistence indicators.

innovators.

All the variables show a considerable degree of heterogeneity, however, as indeed the observed standard deviations are very high, and much higher than the median in most cases. This is not a new finding, since most of the variables considered here are known to be skewed. Yet, our analysis here adds to this known stylised fact that heterogeneity also replicates within persistent innovators, whatever the innovation proxy. We provide further evidence on such heterogeneities by estimating the empirical distribution of growth and key firm characteristics across the different groups of firms.

In Figure 1 we investigate the (unconditional) distribution of sales growth. We report (on a log-scale) the kernel density of firm growth rates G, again pooling over time.[4] Each graph compares persistent innovators and other firms, according to the different innovation proxies. At a general level, we observe that growth rates, in both groups, tend to display fat-tails and tent-shape. This is in agreement with previous evidence on the ubiquity of this empirical stylised fact, and supports the application of regression techniques that can account for the heterogeneous role of innovation persistence along the distribution of sales growth. Perhaps more interesting, and more directly related to our purposes, the kernel estimates do not show any striking difference characterizing persistent innovators. Indeed, a significant degree of overlapping characterizes the densities of the two groups, irrespectively of the selected innovation indicator. This is particularly apparent in the central part of the supports, where the most of the probability mass lies, but it replicates also in the tails. If any difference is to be highlighted, persistent patenters display less dispersed growth rates. although the relatively lower number of firms in this category can play a role in this finding.

The kernel densities of other firm characteristics display more marked differences between persistent innovators and the rest of the sample. Firm size (as employees, in Figure 2) shows

[4]In these as well as in the following density estimates, the kernel function is the Epanenchnikov kernel, and the bandwidth is set according to the "optimal" rule from Silverman (1986).

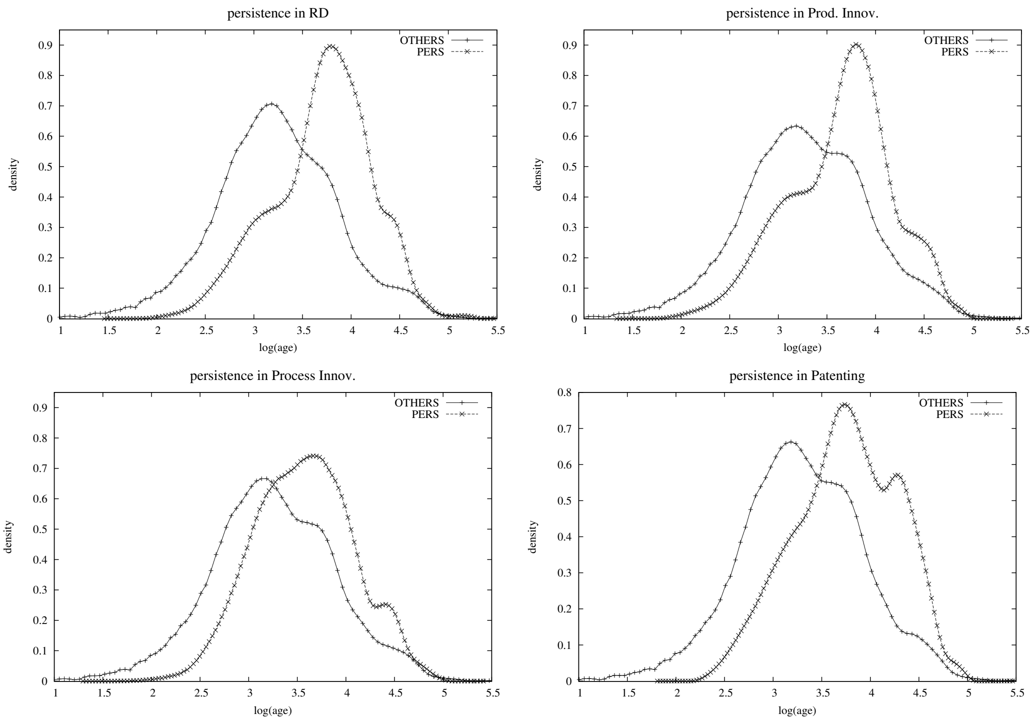

Figure 3: Kernel densities of (log) age, for persistent innovators (PERS) vs. other firms (OTHERS), by different innovation persistence indicators.

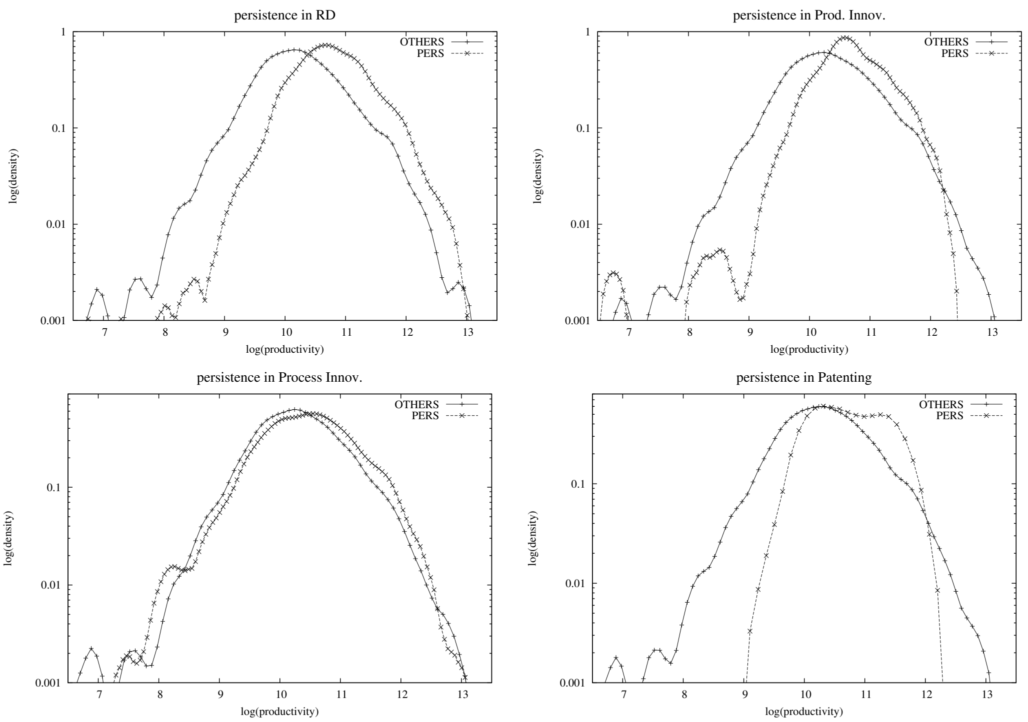

Figure 4: Kernel densities of (log) productivity, for persistent innovators (PERS) vs. other firms (OTHERS), by different innovation persistence indicators.

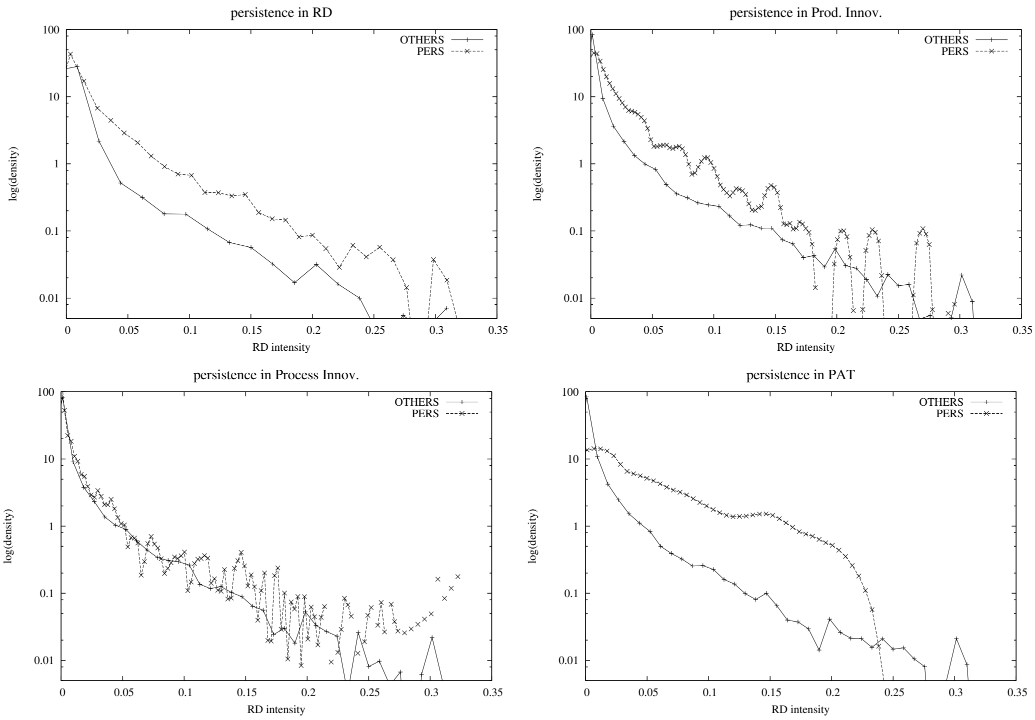

Figure 5: Kernel densities of R&D intensity, as R&D expenses per employee, for persistent innovators (PERS) vs. other firms (OTHERS), by different innovation persistence indicators.

bimodalities in all groups, but the distributions estimated for persistent innovators clearly lay on the right of the distribution estimated across other firms. The same general conclusion emerges for firm age (in Figure 3), where the "right-shift" observed for persistent innovators is even more apparent. And substantially the same finding replicates when comparing labour productivity (in Figure 4). In this case, we also see persistent patenters showing a relatively more concentrated distribution (again, possibly due to the low number of firms in this group). Finally, concerning R&D intensity (in Figure 5), the densities estimated for the different types of persistent innovators all tend to dominate, along the entire support of the variable.

Overall, persistent innovators appear, in distributional terms, comparatively larger, older, more productive and more R&D intense. This finding does not mean, of course, that small, young, low productivity or low R&D intensity firms are not present among persistent innovators.

4 Results

We now present the findings on the two main research questions spelled out in Section 2.

4.1 Persistence of innovation and firm growth

We first report the estimates of the specification in Equation (1), exploring if persistent innovators exhibit any growth premium as compared to other firms. As a benchmark, Table 4 reports the results of a basic model without controls, where sales growth is regressed against each different persistent innovator dummy and a constant term. The estimates highlight significant heterogeneities along the quantiles of the growth rates distribution. Indeed, persistent innovators display a positive growth premium (the coefficient β_1 on the $Pers$ dummies) in the deciles below or up to the median, that is among shrinking or slow-growing firms. Conversely, the growth premium for persistent innovators is negative among high-growth firms in the top

Table 4: Innovation persistence and firm growth - baseline estimates

	OLS	Q10	Q20	Q30	Q40	Q50	Q60	Q70	Q80	Q90
R&D persistent	0.00291	0.0411**	0.0261***	0.0198***	0.00696	0.000920	-0.00246	-0.00922**	-0.0163***	-0.0288***
	(0.00567)	(0.0136)	(0.00791)	(0.00531)	(0.00398)	(0.00363)	(0.00330)	(0.00339)	(0.00463)	(0.00773)
Constant	-0.00695*	-0.281***	-0.150***	-0.0782***	-0.0279***	0.0109***	0.0454***	0.0848***	0.137***	0.231***
	(0.00281)	(0.00555)	(0.00315)	(0.00230)	(0.00187)	(0.00191)	(0.00186)	(0.00194)	(0.00297)	(0.00455)
β_1+Const=0 (p-value):	0.41	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
Product innov. persistence	0.00928	0.0502*	0.0382**	0.0228**	0.00931	0.000761	-0.00243	-0.00975	-0.0228**	-0.0226*
	(0.00880)	(0.0197)	(0.0144)	(0.00766)	(0.00637)	(0.00514)	(0.00464)	(0.00575)	(0.00839)	(0.00974)
Constant	-0.00701**	-0.279***	-0.147***	-0.0754***	-0.0264***	0.0111***	0.0449***	0.0829***	0.134***	0.226***
	(0.00255)	(0.00633)	(0.00357)	(0.00248)	(0.00181)	(0.00179)	(0.00182)	(0.00178)	(0.00238)	(0.00357)
β_1+Const=0 (p-value):	0.78	0.00	0.00	0.01	0.55	0.00	0.00	0.00	0.00	0.00
Process innov. persistence	-0.00139	0.0378**	0.0224**	0.0154**	0.00531	0.00113	-0.00101	-0.00692	-0.0153**	-0.0256**
	(0.00589)	(0.0121)	(0.00818)	(0.00484)	(0.00412)	(0.00356)	(0.00352)	(0.00385)	(0.00504)	(0.00838)
Constant	-0.00597*	-0.281***	-0.150***	-0.0772***	-0.0274***	0.0109***	0.0451***	0.0843***	0.137***	0.230***
	(0.00276)	(0.00494)	(0.00321)	(0.00280)	(0.00206)	(0.00182)	(0.00187)	(0.00192)	(0.00259)	(0.00434)
β_1+Const=0 (p-value):	0.15	0.00	0.00	0.01	0.55	0.00	0.00	0.00	0.00	0.00
Patenting persistence	0.0193	0.0858***	0.0561**	0.0415*	0.0289*	0.0270**	0.0101	-0.000174	-0.0117	-0.0501***
	(0.0156)	(0.0204)	(0.0207)	(0.0163)	(0.0121)	(0.00920)	(0.0103)	(0.0108)	(0.0105)	(0.0130)
Constant	-0.00667**	-0.275***	-0.146***	-0.0744***	-0.0264***	0.0107***	0.0444***	0.0826***	0.133***	0.226***
	(0.00247)	(0.00513)	(0.00340)	(0.00215)	(0.00168)	(0.00169)	(0.00184)	(0.00185)	(0.00228)	(0.00388)
β_1+Const=0 (p-value):	0.41	0.00	0.00	0.08	0.41	0.00	0.00	0.00	0.00	0.00
Observations	12138	12138	12138	12138	12138	12138	12138	12138	12138	12138

Notes: OLS and QR estimates of Equation (1), excluding firm-level and other controls. Standard errors in parenthesis: the OLS standard errors are clustered by firm, while QR standard errors are bootstrapped (100 replications). Asterisks denote significance levels: * p<0.05, ** p<0.01, *** p<0.001.

quantiles. These patterns are robust across the different innovation persistence indicators. Notice also that the growth premium is always smaller in absolute value than the estimated constant terms: thus, the overall average growth of persistent innovators (constant plus β_1) is negative in the bottom quantiles, while it is positive, although weaker than that of the other firms, for high-growth firms in the top quantiles. A simple test of the null $constant + \beta_1 = 0$ confirms this conclusion.

Next, we estimate a full specification of regression (1), where we include all the firm-level controls and the p-score from the first step Probit. Tables 5-8 display the results obtained with the different indicators of innovation persistence. In general, we find a certain degree of heterogeneity in the coefficients on the $Pers$ dummy. If we use R&D to measure persistence (in Table 5), persistent innovators display a negative growth premium along almost the entire distribution of growth rates, and specifically from the third to the ninth decile. Conversely, in the case of product innovation (in Table 6), we do not find any significant difference across persistent innovators and other firms, in all the quantiles. For persistent process innovators (in Table 7), a negative growth premium is found in the top of the growth rates distribution, and no significant effects along the rest of the support. In turn, firms identified as persistent in patenting show a positive premium in the first decile, while a negative and significant one in the top decile (see Table 8).

Overall, the only finding that seems invariant across innovation indicators is the comparatively lower growth performance that persistent innovators display in the top extreme of the distribution of growth rates.

Moving to the control variables, the associated coefficients display interesting non-linearities along the growth quantiles. The patterns are generally consistent across specifications employing different definitions of persistent innovators. Age and size tend to have positive and significant coefficients in the deciles up to the median (with weaker significance for age, though). However, as one moves toward the top of the growth distribution, the association with growth turns negative for age, while not significant for size. Thus, comparatively older and larger firms grow more in the bottom quantiles, while high-growth firms are comparatively younger but not necessarily smaller. Conversely, the estimated coefficients on productivity are rather stable across the quantiles, showing a positive association with sales growth (not always significant in the top decile). Finally, the estimates for R&D intensity are largely un-significant, with the only exception in the top decile in the specification taking R&D to define innovation persistence.

Table 5: R&D persistence and firm growth - full model

	OLS	Q10	Q20	Q30	Q40	Q50	Q60	Q70	Q80	Q90
Persistence dummy	-0.0202**	0.00511	-0.00176	-0.0116**	-0.0135**	-0.00974*	-0.0101*	-0.0145**	-0.0249***	-0.0444***
	(0.00700)	(0.0119)	(0.00635)	(0.00422)	(0.00413)	(0.00441)	(0.00441)	(0.00449)	(0.00548)	(0.0111)
Age	-0.0134**	0.0185*	0.00863	0.00292	-0.00315	-0.00911**	-0.0142***	-0.0194***	-0.0262***	-0.0298***
	(0.00504)	(0.00873)	(0.00492)	(0.00325)	(0.00306)	(0.00323)	(0.00430)	(0.00468)	(0.00597)	(0.00888)
Size (first lag)	0.0149**	0.0415***	0.0272***	0.0204***	0.0132***	0.00723	0.00406	0.00199	0.00516	0.00636
	(0.00494)	(0.00700)	(0.00490)	(0.00390)	(0.00357)	(0.00381)	(0.00491)	(0.00617)	(0.00844)	(0.0126)
Productivity (first lag)	0.0361***	0.0573***	0.0469***	0.0346***	0.0325***	0.0279***	0.0280***	0.0279***	0.0211***	0.0150
	(0.00560)	(0.00759)	(0.00567)	(0.00372)	(0.00310)	(0.00337)	(0.00382)	(0.00473)	(0.00612)	(0.0101)
R&D intensity (first lag)	0.0120	-0.298	-0.219	-0.0285	0.0221	0.00941	0.0147	0.157	0.670	1.970*
	(0.0246)	(0.700)	(0.464)	(0.251)	(0.215)	(0.236)	(0.346)	(0.462)	(0.689)	(0.945)
P-score	-0.0292	-0.240***	-0.141***	-0.102**	-0.0694*	-0.0344	-0.0255	-0.00748	-0.0313	-0.0563
	(0.0383)	(0.0553)	(0.0417)	(0.0317)	(0.0319)	(0.0341)	(0.0440)	(0.0576)	(0.0762)	(0.110)
Constant	-0.493***	-1.121***	-0.819***	-0.587***	-0.476***	-0.349***	-0.287***	-0.217***	-0.0914*	0.0707
	(0.0596)	(0.0729)	(0.0509)	(0.0334)	(0.0251)	(0.0282)	(0.0292)	(0.0344)	(0.0456)	(0.0748)
Observations	11884	11884	11884	11884	11884	11884	11884	11884	11884	11884

Notes: OLS and QR estimates of Equation (1). OLS regressions also include sector and year fixed effects, QR estimates include year fixed effects. Standard errors in parenthesis: the OLS standard errors are clustered by firm, while QR standard errors are bootstrapped (100 replications). Asterisks denote significance levels: * p<0.05, ** p<0.01, *** p<0.001.

Table 6: Product innovation persistence and firm growth - full model

	OLS	Q10	Q20	Q30	Q40	Q50	Q60	Q70	Q80	Q90
Persistence dummy	0.00306	0.0136	0.0111	0.000826	-0.000275	-0.00120	-0.000570	-0.00349	-0.0121	-0.0228
	(0.00909)	(0.0161)	(0.00932)	(0.00707)	(0.00712)	(0.00608)	(0.00513)	(0.00598)	(0.00789)	(0.0161)
Age	-0.0134**	0.0191*	0.0118**	0.00305	-0.00244	-0.00951***	-0.0146***	-0.0200***	-0.0263***	-0.0357***
	(0.00486)	(0.00828)	(0.00446)	(0.00380)	(0.00307)	(0.00286)	(0.00341)	(0.00367)	(0.00492)	(0.00658)
Size (first lag)	0.0178***	0.0368***	0.0261***	0.0193***	0.0134***	0.00899***	0.00740**	0.00502	0.00566	-0.00887
	(0.00456)	(0.00621)	(0.00393)	(0.00294)	(0.00248)	(0.00242)	(0.00279)	(0.00283)	(0.00364)	(0.00724)
Productivity (first lag)	0.0308***	0.0542***	0.0417***	0.0323***	0.0284***	0.0256***	0.0241***	0.0239***	0.0175***	0.0205*
	(0.00582)	(0.00936)	(0.00532)	(0.00440)	(0.00372)	(0.00373)	(0.00403)	(0.00367)	(0.00497)	(0.00914)
R&D intensity (first lag)	0.0360	-0.763	-0.263	0.00746	0.0492	0.0292	0.0349	0.0721	0.517	1.529
	(0.0272)	(0.663)	(0.465)	(0.228)	(0.147)	(0.112)	(0.174)	(0.285)	(0.522)	(0.850)
P-score	-0.163*	-0.448***	-0.332***	-0.238***	-0.188***	-0.125**	-0.119*	-0.0830	-0.131	0.0971
	(0.0754)	(0.105)	(0.0778)	(0.0460)	(0.0390)	(0.0420)	(0.0483)	(0.0555)	(0.0760)	(0.141)
Constant	-0.403***	-1.156***	-0.815***	-0.580***	-0.438***	-0.319***	-0.229***	-0.158***	-0.00882	0.127
	(0.0523)	(0.0770)	(0.0465)	(0.0396)	(0.0323)	(0.0341)	(0.0324)	(0.0317)	(0.0440)	(0.0761)
Observations	11868	11868	11868	11868	11868	11868	11868	11868	11868	11868

Notes: OLS and QR estimates of Equation (1). OLS regressions also include sector and year fixed effects, QR estimates include year fixed effects. Standard errors in parenthesis: the OLS standard errors are clustered by firm, while QR standard errors are bootstrapped (100 replications). Asterisks denote significance levels: * $p<0.05$, ** $p<0.01$, *** $p<0.001$.

Table 7: Process innovation persistence and firm growth - full model

	OLS	Q10	Q20	Q30	Q40	Q50	Q60	Q70	Q80	Q90
Persistence dummy	-0.00707	0.0130	0.00723	0.00324	0.000843	0.00331	0.000726	-0.00376	-0.00933	-0.0211*
	(0.00562)	(0.00985)	(0.00526)	(0.00445)	(0.00382)	(0.00359)	(0.00349)	(0.00407)	(0.00569)	(0.0101)
Age	-0.00964	0.0238*	0.0144*	0.00665	-0.000194	-0.00678*	-0.0118**	-0.0182***	-0.0237***	-0.0356***
	(0.00564)	(0.0105)	(0.00597)	(0.00407)	(0.00386)	(0.00339)	(0.00403)	(0.00435)	(0.00586)	(0.00977)
Size (first lag)	0.0183***	0.0400***	0.0275***	0.0206***	0.0134***	0.00951**	0.00602	0.00391	0.00606	-0.000543
	(0.00511)	(0.00824)	(0.00513)	(0.00390)	(0.00314)	(0.00329)	(0.00364)	(0.00431)	(0.00551)	(0.0105)
Productivity (first lag)	0.0312***	0.0550***	0.0434***	0.0318***	0.0293***	0.0261***	0.0253***	0.0252***	0.0189***	0.0138
	(0.00591)	(0.00989)	(0.00588)	(0.00413)	(0.00335)	(0.00340)	(0.00371)	(0.00456)	(0.00537)	(0.0104)
R&D intensity (first lag)	0.0260	-0.550	-0.290	-0.0116	0.0344	0.0222	0.0241	0.124	0.484	1.539
	(0.0257)	(0.614)	(0.271)	(0.157)	(0.142)	(0.117)	(0.230)	(0.371)	(0.646)	(0.919)
P-score	-0.120*	-0.351***	-0.246***	-0.191***	-0.137***	-0.108**	-0.0806	-0.0556	-0.0946	-0.0303
	(0.0603)	(0.0945)	(0.0602)	(0.0418)	(0.0380)	(0.0397)	(0.0441)	(0.0627)	(0.0874)	(0.149)
Constant	-0.452***	-1.094***	-0.787***	-0.563***	-0.444***	-0.335***	-0.269***	-0.194***	-0.0713	0.123
	(0.0596)	(0.0741)	(0.0482)	(0.0355)	(0.0307)	(0.0317)	(0.0308)	(0.0368)	(0.0463)	(0.0723)
Observations	11884	11884	11884	11884	11884	11884	11884	11884	11884	11884

Notes: OLS and QR estimates of Equation (1). OLS regressions also include sector and year fixed effects, QR estimates include year fixed effects. Standard errors in parenthesis: the OLS standard errors are clustered by firm, while QR standard errors are bootstrapped (100 replications). Asterisks denote significance levels: * p<0.05, ** p<0.01, *** p<0.001.

Table 8: Patenting persistence and firm growth - full model

	OLS	Q10	Q20	Q30	Q40	Q50	Q60	Q70	Q80	Q90
Persistence dummy	0.00425	0.0585*	0.0197	0.0127	0.0189	0.0200*	0.00836	0.00391	-0.0302	-0.0705**
	(0.0128)	(0.0277)	(0.0144)	(0.0142)	(0.0108)	(0.00886)	(0.0104)	(0.0148)	(0.0189)	(0.0266)
Age	-0.0186*	0.0107	-0.00158	-0.000892	-0.00798	-0.0125**	-0.0184**	-0.0219***	-0.0317***	-0.0557***
	(0.00753)	(0.0128)	(0.00823)	(0.00621)	(0.00536)	(0.00473)	(0.00594)	(0.00576)	(0.00864)	(0.0154)
Size (first lag)	0.00890***	0.0154***	0.0102***	0.00566***	0.00285*	0.000658	-0.000370	-0.000249	-0.000447	-0.00309
	(0.00226)	(0.00355)	(0.00215)	(0.00172)	(0.00135)	(0.00135)	(0.00155)	(0.00166)	(0.00225)	(0.00361)
Productivity (first lag)	0.0374***	0.0663***	0.0551***	0.0398***	0.0357***	0.0303***	0.0294***	0.0272***	0.0224***	0.0221*
	(0.00605)	(0.00775)	(0.00543)	(0.00413)	(0.00320)	(0.00294)	(0.00375)	(0.00415)	(0.00614)	(0.00987)
R&D intensity (first lag)	-0.00622	-0.843	-0.332	-0.0928	-0.0623	0.00154	0.00521	0.0336	0.458	1.475
	(0.0238)	(0.648)	(0.461)	(0.245)	(0.170)	(0.133)	(0.196)	(0.326)	(0.560)	(0.828)
P-score	0.0199	-0.181	-0.0384	-0.0358	0.000426	0.000193	0.0178	0.00486	0.0383	0.260
	(0.0961)	(0.159)	(0.112)	(0.0833)	(0.0710)	(0.0677)	(0.0744)	(0.0805)	(0.114)	(0.197)
Constant	-0.471***	-1.108***	-0.826***	-0.590***	-0.464***	-0.343***	-0.278***	-0.198***	-0.0753	0.0885
	(0.0616)	(0.0711)	(0.0494)	(0.0398)	(0.0301)	(0.0267)	(0.0312)	(0.0350)	(0.0517)	(0.0741)
Observations	11884	11884	11884	11884	11884	11884	11884	11884	11884	11884

Notes: OLS and QR estimates of Equation (1). OLS regressions also include sector and year fixed effects, QR estimates include year fixed effects. Standard errors in parenthesis: the OLS standard errors are clustered by firm, while QR standard errors are bootstrapped (100 replications). Asterisks denote significance levels: * p<0.05, ** p<0.01, *** p<0.001.

4.2 Persistence of innovation and persistence of firm growth

We next report the estimates of the regression in Equation (2), where we explore if innovation persistence relates to persistence of growth. Recall that in this regression model the coefficient on lagged growth G_{t-1} captures the degree of autocorrelation in sales growth for firms that are not persistent innovators ($Pers$=0), while we are mostly interested in the additional "growth persistence premium" given by the coefficient on the interaction term. We focus the comments on these factors.[5]

In Table 9 we report the estimates of a benchmark model without controls, where sales growth is regressed against its lag G_{t-1}, the persistence innovation dummies and the interaction between the two. For firms that are not in the group of persistent innovators, growth autocorrelation tends to be positive up to the 6^{th} decile, while anti-correlation emerges among high-growth firms in the top quantiles. This pattern emerges independently from the innovation indicator considered. Notice, however, that the estimated coefficients are always relatively small (never above 0.1 in absolute value), thus confirming previous studies reporting that growth rates are essentially uncorrelated over time. On the other hand, persistent innovators do not display any differential persistence in their growth patterns as compared to other firms. In fact, the estimated coefficients on the interaction terms are never significant. Also this finding is robust across the different measures of innovation persistence.

The main patterns replicate when we estimate the full models including the firm-level controls, reported in Tables 10-13. First, concerning firms that are not persistent innovators, the estimates on G_{t-1} lose some significance in the central quantiles, but we still confirm a positive (mild) autocorrelation of growth in the left part of the growth rates distribution and a (mild) anti-correlation in the top quantiles. Moreover, persistent innovators do not display any difference in the degree of growth autocorrelation as compared to the other firms, no matter the innovation persistence indicator considered.

Regarding the controls, the findings are broadly consistent with the results emerging from the estimates of the model without interactions. Age tend to display a positive association with growth in the left part of the growth rates distribution, and in particular in the first decile, while a negative association with growth emerges in the top quantiles. Firm size has positive coefficient estimates in the left half of the growth rates support, while for productivity the coefficients tend to be positive along all the quantiles. Thus, the relatively younger, smaller and more productive firms grow more among high-growth firms, while among slow-growing or shirking firms we find that growth is favored by being older, larger and more productive. Finally, R&D intensity does not display any statistically significant coefficient, in none of the quantiles.[6]

[5]The coefficient on the $Pers$ dummy captures the growth premium for the group of persistent innovators that have zero lagged growth, and it is as such less interesting.

[6]Since there might be doubts that the current crisis plays a role in the results, in unreported robustness checks we re-estimated all the specifications of both Equation (1) and Equation (2) without considering the years 2009-2012. The results, available upon request, are practically unchanged as compared to the estimates reported here.

Table 9: Persistence of innovation and persistence of growth - baseline estimates

	OLS	Q10	Q20	Q30	Q40	Q50	Q60	Q70	Q80	Q90
R&D persistence	0.00347	0.0290*	0.0226**	0.0209***	0.0105*	0.00415	0.00145	-0.00561	-0.0143**	-0.0246**
	(0.00633)	(0.0132)	(0.00851)	(0.00598)	(0.00415)	(0.00376)	(0.00324)	(0.00374)	(0.00544)	(0.00818)
Sales growth (first lag)	-0.0365	0.0741***	0.0621***	0.0655***	0.0507***	0.0397**	0.0377**	0.0137	-0.0203	-0.0717***
	(0.0313)	(0.0199)	(0.0122)	(0.0121)	(0.00970)	(0.0149)	(0.0115)	(0.0134)	(0.0128)	(0.0196)
Interaction	0.00757	0.0307	0.00107	-0.00395	-0.0207	-0.0238	-0.0262	-0.00632	0.0120	0.0170
	(0.0516)	(0.0456)	(0.0443)	(0.0323)	(0.0252)	(0.0223)	(0.0211)	(0.0192)	(0.0230)	(0.0453)
Constant	-0.0158***	-0.295***	-0.161***	-0.0891***	-0.0359***	0.00315	0.0384***	0.0780***	0.131***	0.226***
	(0.00314)	(0.00667)	(0.00333)	(0.00274)	(0.00212)	(0.00204)	(0.00170)	(0.00214)	(0.00318)	(0.00449)
Prod innov. persistence	0.00962	0.0440*	0.0399*	0.0191	0.0118	0.00197	0.00143	-0.00789	-0.0211**	-0.0214*
	(0.00923)	(0.0214)	(0.0172)	(0.0113)	(0.00754)	(0.00575)	(0.00582)	(0.00569)	(0.00793)	(0.0105)
Sales growth (first lag)	-0.0358	0.0769***	0.0614***	0.0640***	0.0474***	0.0309**	0.0272*	0.00674	-0.0209	-0.0701***
	(0.0261)	(0.0187)	(0.0127)	(0.0145)	(0.0101)	(0.0119)	(0.0121)	(0.0107)	(0.0128)	(0.0199)
Interaction	0.0550	0.0406	0.0533	0.0319	0.0165	0.0179	0.00355	0.00827	0.0167	0.116
	(0.0635)	(0.125)	(0.0900)	(0.0697)	(0.0421)	(0.0571)	(0.0534)	(0.0477)	(0.0498)	(0.0603)
Constant	-0.0157***	-0.292***	-0.158***	-0.0859***	-0.0346***	0.00381*	0.0385***	0.0775***	0.129***	0.222***
	(0.00285)	(0.00653)	(0.00303)	(0.00291)	(0.00212)	(0.00181)	(0.00162)	(0.00204)	(0.00253)	(0.00477)
Proc innov. persistence	0.000162	0.0287*	0.0172*	0.0168**	0.00503	0.000436	0.00101	-0.00792	-0.0161**	-0.0279**
	(0.00675)	(0.0138)	(0.00775)	(0.00615)	(0.00492)	(0.00427)	(0.00373)	(0.00442)	(0.00549)	(0.00980)
Sales growth (first lag)	-0.0185	0.0741***	0.0610***	0.0661***	0.0475***	0.0339*	0.0323*	0.00767	-0.0221	-0.0722***
	(0.0252)	(0.0211)	(0.0143)	(0.0145)	(0.0118)	(0.0138)	(0.0138)	(0.0148)	(0.0138)	(0.0189)
Interaction	-0.0471	0.0111	-0.000396	-0.0144	0.00274	-0.00363	-0.00934	-0.0000734	0.0233	0.0285
	(0.0615)	(0.0423)	(0.0414)	(0.0375)	(0.0302)	(0.0326)	(0.0260)	(0.0246)	(0.0254)	(0.0489)
Constant	-0.0150***	-0.294***	-0.159***	-0.0883***	-0.0348***	0.00412	0.0387***	0.0787***	0.131***	0.227***
	(0.00304)	(0.00638)	(0.00281)	(0.00307)	(0.00266)	(0.00237)	(0.00209)	(0.00249)	(0.00330)	(0.00497)
Persistence dummy	0.0227	0.118***	0.0631***	0.0412**	0.0237*	0.0118	0.0121	0.00800	-0.0150	-0.0434
	(0.0174)	(0.0205)	(0.0166)	(0.0149)	(0.0109)	(0.0133)	(0.0117)	(0.0115)	(0.0142)	(0.0264)
Sales growth (first lag)	-0.0347	0.0765***	0.0606***	0.0625***	0.0471***	0.0307*	0.0285*	0.00679	-0.0199	-0.0653**
	(0.0254)	(0.0189)	(0.0116)	(0.0140)	(0.0106)	(0.0122)	(0.0119)	(0.0102)	(0.0132)	(0.0204)
Interaction	0.0402	0.126	0.182	0.101	0.161	0.154	-0.0123	-0.0445	-0.00816	-0.0766
	(0.156)	(0.104)	(0.0999)	(0.110)	(0.107)	(0.119)	(0.107)	(0.0930)	(0.0930)	(0.200)
Constant	-0.0154***	-0.291***	-0.157***	-0.0857***	-0.0341***	0.00371*	0.0384***	0.0771***	0.128***	0.222***
	(0.00276)	(0.00537)	(0.00249)	(0.00233)	(0.00198)	(0.00183)	(0.00168)	(0.00195)	(0.00254)	(0.00444)
Observations	10554	10554	10554	10554	10554	10554	10554	10554	10554	10554

Notes: OLS and QR estimates of Equation (2), excluding firm-level and other controls. Standard errors in parenthesis: the OLS standard errors are clustered by firm, while QR standard errors are bootstrapped (100 replications). Asterisks denote significance levels: * p<0.05, ** p<0.01, *** p<0.001.

Table 10: R&D persistence and persistence of growth - full model

	OLS	Q10	Q20	Q30	Q40	Q50	Q60	Q70	Q80	Q90
Persistence dummy	-0.0196*	0.0109	0.00332	-0.0105*	-0.0116*	-0.00840	-0.00763	-0.0125*	-0.0225**	-0.0445**
	(0.00805)	(0.0125)	(0.00773)	(0.00489)	(0.00467)	(0.00530)	(0.00516)	(0.00605)	(0.00817)	(0.0154)
Sales growth (first lag)	-0.0754*	0.0193	0.0357	0.0407***	0.0293***	0.0220	0.0184	-0.00512	-0.0183	-0.0622**
	(0.0322)	(0.0214)	(0.0193)	(0.0114)	(0.00879)	(0.0120)	(0.0124)	(0.0170)	(0.0158)	(0.0198)
Interaction	0.0186	-0.0224	-0.000317	0.000170	0.0103	-0.00102	-0.0108	-0.0123	-0.0154	-0.00368
	(0.0521)	(0.0460)	(0.0313)	(0.0207)	(0.0212)	(0.0235)	(0.0239)	(0.0265)	(0.0246)	(0.0400)
Age	-0.0137*	0.0224*	0.00915	0.00610	0.000188	-0.00728	-0.0136**	-0.0186***	-0.0260***	-0.0310**
	(0.00592)	(0.00937)	(0.00603)	(0.00421)	(0.00394)	(0.00396)	(0.00479)	(0.00475)	(0.00633)	(0.0103)
Size (first lag)	0.0159**	0.0435***	0.0279***	0.0229***	0.0132**	0.00750	0.00609	0.00502	0.00905	0.00620
	(0.00558)	(0.00801)	(0.00503)	(0.00444)	(0.00434)	(0.00589)	(0.00661)	(0.00840)	(0.00896)	(0.0110)
Productivity (first lag)	0.0401***	0.0575***	0.0486***	0.0313***	0.0316***	0.0277***	0.0292***	0.0275***	0.0219***	0.0202*
	(0.00645)	(0.00879)	(0.00656)	(0.00454)	(0.00413)	(0.00410)	(0.00432)	(0.00549)	(0.00634)	(0.00945)
R&D intensity (first lag)	0.0136	-0.688	-0.252	-0.0267	-0.0475	-0.0174	0.00127	0.311	0.893	1.943*
	(0.0294)	(0.804)	(0.523)	(0.375)	(0.351)	(0.440)	(0.567)	(0.673)	(0.756)	(0.839)
P-score	-0.0389	-0.243***	-0.151**	-0.115**	-0.0677	-0.0375	-0.0380	-0.0340	-0.0636	-0.0488
	(0.0438)	(0.0691)	(0.0487)	(0.0409)	(0.0424)	(0.0542)	(0.0613)	(0.0772)	(0.0826)	(0.102)
Constant	-0.400***	-1.144***	-0.842***	-0.572***	-0.477***	-0.355***	-0.308***	-0.224***	-0.112*	0.0228
	(0.0589)	(0.0782)	(0.0610)	(0.0413)	(0.0374)	(0.0328)	(0.0314)	(0.0382)	(0.0486)	(0.0803)
Observations	10346	10346	10346	10346	10346	10346	10346	10346	10346	10346

Notes: OLS and QR estimates of Equation (2). OLS regressions also include sector and year fixed effects, QR estimates include year fixed effects.Standard errors in parenthesis: the OLS standard errors are clustered by firm, while QR standard errors are bootstrapped (100 replications). Asterisks denote significance levels: * p<0.05, ** p<0.01, *** p<0.001.

Table 11: Product innovation persistence and persistence of growth - full model

	OLS	Q10	Q20	Q30	Q40	Q50	Q60	Q70	Q80	Q90
Persistence dummy	0.00432	0.0373*	0.0107	0.0125	0.00767	0.00734	0.00123	-0.00822	-0.0243**	-0.0393**
	(0.00991)	(0.0179)	(0.0101)	(0.00693)	(0.00661)	(0.00709)	(0.00552)	(0.00732)	(0.00787)	(0.0147)
Sales growth (first lag)	-0.0708*	0.0135	0.0333*	0.0438***	0.0321***	0.0241*	0.0141	-0.00613	-0.0218	-0.0645***
	(0.0277)	(0.0198)	(0.0145)	(0.00854)	(0.00776)	(0.0101)	(0.0107)	(0.0128)	(0.0130)	(0.0173)
Interaction	0.0466	-0.0144	-0.0269	-0.0654	-0.00271	0.0000206	0.0253	0.0447	0.0760	0.125**
	(0.0595)	(0.0947)	(0.0778)	(0.0561)	(0.0408)	(0.0390)	(0.0378)	(0.0435)	(0.0434)	(0.0477)
Age	-0.0130*	0.0201*	0.00887	0.00627	-0.00148	-0.00786*	-0.0127***	-0.0198***	-0.0268***	-0.0398***
	(0.00564)	(0.00915)	(0.00547)	(0.00437)	(0.00347)	(0.00318)	(0.00354)	(0.00340)	(0.00463)	(0.00773)
Size (first lag)	0.0205***	0.0431***	0.0282***	0.0212***	0.0133***	0.00813**	0.00751*	0.00580	0.00689	-0.00174
	(0.00511)	(0.00608)	(0.00446)	(0.00368)	(0.00273)	(0.00311)	(0.00312)	(0.00337)	(0.00424)	(0.00802)
Productivity (first lag)	0.0335***	0.0534***	0.0448***	0.0274***	0.0272***	0.0254***	0.0259***	0.0250***	0.0189***	0.0210*
	(0.00663)	(0.00866)	(0.00582)	(0.00451)	(0.00437)	(0.00430)	(0.00430)	(0.00486)	(0.00546)	(0.00994)
R&D intensity (first lag)	0.0478	-1.268	-0.204	-0.0554	-0.0198	-0.00544	0.0108	0.223	0.756	1.933*
	(0.0319)	(0.680)	(0.339)	(0.214)	(0.137)	(0.153)	(0.274)	(0.450)	(0.738)	(0.808)
P-score	-0.216*	-0.523***	-0.350***	-0.268***	-0.184***	-0.116*	-0.138**	-0.106	-0.133	-0.0319
	(0.0849)	(0.115)	(0.0813)	(0.0630)	(0.0434)	(0.0477)	(0.0500)	(0.0637)	(0.0848)	(0.152)
Constant	-0.385***	-1.089***	-0.802***	-0.527***	-0.425***	-0.329***	-0.279***	-0.196***	-0.0713	0.0631
	(0.0686)	(0.0774)	(0.0464)	(0.0377)	(0.0373)	(0.0369)	(0.0355)	(0.0415)	(0.0462)	(0.0808)
Observations	10334	10334	10334	10334	10334	10334	10334	10334	10334	10334

Notes: OLS and QR estimates of Equation (2). OLS regressions also include sector and year fixed effects, QR estimates include year fixed effects. Standard errors in parenthesis: the OLS standard errors are clustered by firm, while QR standard errors are bootstrapped (100 replications). Asterisks denote significance levels: * $p<0.05$, ** $p<0.01$, *** $p<0.001$.

Table 12: Process innovation persistence and persistence of growth - full model

	OLS	Q10	Q20	Q30	Q40	Q50	Q60	Q70	Q80	Q90
Persistence dummy	-0.00517	0.0176	0.00434	0.00357	0.00273	0.00322	0.00106	-0.00363	-0.00762	-0.0211
	(0.00652)	(0.00968)	(0.00503)	(0.00477)	(0.00398)	(0.00387)	(0.00423)	(0.00436)	(0.00523)	(0.0112)
Sales growth (first lag)	-0.0569*	0.0183	0.0356	0.0444***	0.0312***	0.0198	0.0166	-0.00472	-0.0148	-0.0648***
	(0.0264)	(0.0262)	(0.0192)	(0.0110)	(0.00834)	(0.0114)	(0.0107)	(0.0161)	(0.0167)	(0.0189)
Interaction	-0.0356	-0.0207	-0.000695	-0.0121	0.00790	0.0147	0.00354	0.000176	-0.00887	0.00899
	(0.0624)	(0.0460)	(0.0299)	(0.0227)	(0.0185)	(0.0237)	(0.0218)	(0.0281)	(0.0292)	(0.0385)
Age	-0.00888	0.0267*	0.0143*	0.0105*	0.00314	-0.00510	-0.0101*	-0.0175**	-0.0224**	-0.0354**
	(0.00655)	(0.0112)	(0.00706)	(0.00450)	(0.00406)	(0.00363)	(0.00500)	(0.00588)	(0.00725)	(0.0121)
Size (first lag)	0.0202***	0.0438***	0.0296***	0.0230***	0.0146***	0.0100**	0.00815	0.00622	0.00829	0.00224
	(0.00581)	(0.00701)	(0.00499)	(0.00410)	(0.00344)	(0.00374)	(0.00416)	(0.00546)	(0.00703)	(0.0103)
Productivity (first lag)	0.0343***	0.0573***	0.0452***	0.0277***	0.0269***	0.0247***	0.0261***	0.0247***	0.0179**	0.0178
	(0.00673)	(0.00890)	(0.00652)	(0.00458)	(0.00411)	(0.00430)	(0.00453)	(0.00553)	(0.00683)	(0.0119)
R&D intensity (first lag)	0.0315	-0.954	-0.228	-0.00673	-0.0320	-0.0325	-0.0118	0.250	0.758	1.914*
	(0.0309)	(0.716)	(0.569)	(0.306)	(0.208)	(0.261)	(0.408)	(0.625)	(0.791)	(0.854)
P-score	-0.146*	-0.396***	-0.263***	-0.212***	-0.150***	-0.105*	-0.104	-0.0820	-0.122	-0.0702
	(0.0693)	(0.0914)	(0.0660)	(0.0462)	(0.0447)	(0.0499)	(0.0591)	(0.0853)	(0.108)	(0.148)
Constant	-0.361***	-1.132***	-0.813***	-0.538***	-0.434***	-0.330***	-0.283***	-0.198***	-0.0720	0.0776
	(0.0584)	(0.0729)	(0.0531)	(0.0374)	(0.0343)	(0.0357)	(0.0348)	(0.0410)	(0.0555)	(0.0926)
Observations	10346	10346	10346	10346	10346	10346	10346	10346	10346	10346

Notes: OLS and QR estimates of Equation (2). OLS regressions also include sector and year fixed effects, QR estimates include year fixed effects. Standard errors in parenthesis: the OLS standard errors are clustered by firm, while QR standard errors are bootstrapped (100 replications). Asterisks denote significance levels: * p<0.05, ** p<0.01, *** p<0.001.

Table 13: Patenting persistence and persistence of growth - full model

	OLS	Q10	Q20	Q30	Q40	Q50	Q60	Q70	Q80	Q90
Persistence dummy	0.0108	0.0602*	0.0281	0.0253	0.0237	0.0224	0.00989	-0.000488	-0.0326	-0.0967**
	(0.0157)	(0.0269)	(0.0175)	(0.0168)	(0.0161)	(0.0114)	(0.0143)	(0.0156)	(0.0204)	(0.0344)
Sales growth (first lag)	-0.0687*	0.0178	0.0400**	0.0402***	0.0316***	0.0250**	0.0193	-0.00229	-0.0207	-0.0676***
	(0.0270)	(0.0209)	(0.0142)	(0.0102)	(0.00752)	(0.00867)	(0.00994)	(0.0132)	(0.0138)	(0.0158)
Interaction	-0.0421	0.124	0.0481	0.0174	-0.0262	-0.0395	0.0135	0.0170	-0.0511	-0.0286
	(0.128)	(0.154)	(0.143)	(0.0943)	(0.0928)	(0.0704)	(0.0916)	(0.110)	(0.137)	(0.231)
Age	-0.0190*	0.0182	0.00424	0.00441	-0.00483	-0.0101*	-0.0155*	-0.0210***	-0.0333***	-0.0597***
	(0.00906)	(0.0128)	(0.00863)	(0.00704)	(0.00569)	(0.00503)	(0.00646)	(0.00553)	(0.00874)	(0.0170)
Size (first lag)	0.00885***	0.0174***	0.0108***	0.00682***	0.00340*	0.00128	0.000143	-0.000202	-0.000492	-0.00323
	(0.00251)	(0.00340)	(0.00230)	(0.00192)	(0.00148)	(0.00145)	(0.00153)	(0.00178)	(0.00215)	(0.00337)
Productivity (first lag)	0.0415***	0.0685***	0.0542***	0.0366***	0.0333***	0.0296***	0.0303***	0.0277***	0.0242***	0.0304**
	(0.00697)	(0.00958)	(0.00574)	(0.00459)	(0.00372)	(0.00387)	(0.00414)	(0.00433)	(0.00556)	(0.0108)
R&D intensity (first lag)	-0.00577	-1.495*	-0.256	-0.269	-0.0597	-0.0702	-0.0281	0.127	0.670	1.877*
	(0.0280)	(0.685)	(0.558)	(0.330)	(0.176)	(0.162)	(0.253)	(0.439)	(0.671)	(0.790)
P-score	0.00949	-0.312	-0.103	-0.0669	-0.0139	-0.0131	-0.0158	-0.0132	0.0532	0.305
	(0.114)	(0.161)	(0.115)	(0.0918)	(0.0711)	(0.0679)	(0.0753)	(0.0746)	(0.114)	(0.219)
Constant	-0.381***	-1.149***	-0.836***	-0.576***	-0.451***	-0.347***	-0.297***	-0.205***	-0.0906	0.0136
	(0.0601)	(0.0863)	(0.0527)	(0.0413)	(0.0368)	(0.0342)	(0.0335)	(0.0369)	(0.0483)	(0.0815)
Observations	10346	10346	10346	10346	10346	10346	10346	10346	10346	10346

Notes: OLS and QR estimates of Equation (2). OLS regressions also include sector and year fixed effects, QR estimates include year fixed effects. Standard errors in parenthesis: the OLS standard errors are clustered by firm, while QR standard errors are bootstrapped (100 replications). Asterisks denote significance levels: * p<0.05, ** p<0.01, *** p<0.001.

5 Conclusion

Persistent innovators are often under the lenses of academic scholars and policy makers as a potential source of positive contributions to the economic performance of sectors and countries. While a large literature studies the empirical relevance, the characteristics and the factors that sustain persistently innovative firms, there is limited empirical effort to verify if it is indeed the case that persistent innovators display peculiar growth trajectories, outperforming the other firms populating the economy as theory would generally suggest. The analysis developed here contributes to fill this empirical gap.

From a methodological point of view, we exploit a long-in-time dataset of Spanish firms to introduce a novel approach to the identification of persistent innovators, overcoming some limitations of previous persistence indicators based on innovation surveys. The "long-run" perspective allowed by the data is also important to tackle the potential joint determination of firm growth and the definition of persistent innovators itself.

We exploit this empirical setting to ask whether persistent innovators grow more than other firms, and if innovation persistence is associated to higher growth persistence. While previous studies provide (scant) evidence on the former research question, this study is the first – to our knowledge at least – that jointly analyses innovation persistence and persistence of firm growth. We also compare growth trajectories across different definitions of persistent innovators, based on different innovative activities undertaken by firms, in terms of R&D expenditure, product or process innovation, and patenting.

Taking the more robust estimates that we present here, our findings provide a negative answer to our main research questions. First, concerning the differences in average growth, we find some heterogeneities across innovation persistence indicators. Persistent R&D innovators grow less than the other firms along most of the quantiles of the firm growth rates distribution. An equally "negative growth premium" characterizes persistent innovators among high-growth firms in the top-quantiles, if we take process innovation or patenting as the indicators to define persistent innovators, whereas we do not find differences with other firms if we take persistence in the ability to introduce new products, along all the quantiles. A fair reading of such heterogeneities is that persistent innovators do not certainly grow more, and they may even grow less than other firms.

Further, the ability to persistently innovate does not associate with higher persistence in growth rates: independently from the innovation indicator considered, persistent innovators do not show any statistically significant difference in the degree of growth autocorrelation, neither among slow-growing and possibly shrinking firms in the bottom quantiles, nor among fast-growing firms.

References

Antonelli, C., F. Crespi, and G. Scellato (2013): "Internal and external factors in innovation persistence," *Economics of Innovation and New Technology*, 22, 256–280.

Audretsch, D. B., A. Coad, and A. Segarra (2014): "Firm growth and innovation," *Small Business Economics*, 43, 743–749.

Bas, C. and W. Latham (2009): *The economics of persistent innovation: An evolutionary view*, vol. 31, Springer Science & Business Media.

Beneito, P., P. Coscollá-Girona, M. E. Rochina-Barrachina, and A. Sanchis (2015): "Competitive pressure and innovation at the firm level," *The Journal of Industrial Economics*, 63, 422–457.

Bianchini, S., G. Pellegrino, and F. Tamagni (2016): "Innovation Strategies and Firm Growth," LEM Working Papers 2016/03, Laboratory of Economics and Management (LEM), Sant'Anna School of Advanced Studies, Pisa, Italy.

Bottazzi, G., G. Dosi, N. Jacoby, A. Secchi, and F. Tamagni (2010): "Corporate performances and market selection: some comparative evidence," *Industrial and Corporate Change*, 19, 1953–1996.

Bottazzi, G., G. Dosi, M. Lippi, F. Pammolli, and M. Riccaboni (2001): "Innovation and corporate growth in the evolution of the drug industry," *International Journal of Industrial Organization*, 19, 1161–1187.

Bottazzi, G. and A. Secchi (2006): "Explaining the distribution of firm growth rates," *The RAND Journal of Economics*, 37, 235–256.

Cefis, E. and M. Ciccarelli (2005): "Profit differentials and innovation," *Economics of Innovation and New Technology*, 14, 43–61.

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

Coad, A., A. Segarra, and M. Teruel (2016): "Innovation and Firm Growth: Does Age Play a role?" *Research Policy*, 45, 387–400.

Colombelli, A., N. Haned, and C. Le Bas (2013): "On firm growth and innovation: Some new empirical perspectives using French CIS (1992–2004)," *Structural Change and Economic Dynamics*, 26, 14–26.

Demirel, P. and M. Mazzucato (2012): "Innovation and firm growth: Is R&D worth it?" *Industry and Innovation*, 19, 45–62.

Deschryvere, M. (2014): "R&D, firm growth and the role of innovation persistence: an analysis of Finnish SMEs and large firms," *Small Business Economics*, 43, 767–785.

Dosi, G., D. Moschella, E. Pugliese, and F. Tamagni (2015): "Productivity, market selection, and corporate growth: comparative evidence across US and Europe," *Small Business Economics*, 45, 643–672.

Duguet, E. and S. Monjon (2004): "Is innovation persistent at the firm level? An econometric examination comparing the propensity score and regression methods," *An Econometric Examination Comparing the Propensity Score and Regression Methods (July 2004). University of Paris I-Cahiers de la MSE Working Paper*, 75.

Falk, M. (2012): "Quantile estimates of the impact of R&D intensity on firm performance," *Small Business Economics*, 39, 19–37.

Fariñas, J. C., A. López, and A. Martín-Marcos (2015): "Sourcing strategies and productivity: evidence for Spanish manufacturing firms," *BRQ Business Research Quarterly.*

Freel, M. S. (2000): "Do Small Innovating Firms Outperform Non-Innovators?" *Small Business Economics*, 14, 195–210.

Geroski, P. A. (2002): "The Growth of Firms in Theory and in Practice," in *Competence, Governance, and Entrepreneurship - Advances in Economic Strategy Research*, ed. by N. Foss and V. Mahnke, Oxford University Press: Oxford and New York.

Geroski, P. A., J. Van Reenen, and C. F. Walters (1997): "How persistently do firms innovate?" *Research Policy*, 26, 33–48.

Hölzl, W. (2009): "Is the R&D behaviour of fast-growing SMEs different? Evidence from CIS III data for 16 countries," *Small Business Economics*, 33, 59–75.

Jaumandreu, J. and J. C. Farinas (1999): "Dies anos de encuesta sobre estrategias empresariales (ESEE)," *Economia Industrial*, 329, 29–42.

Koenker, R. and J. Bassett, Gilbert (1978): "Regression Quantiles," *Econometrica*, 46, 33–50.

Le Bas, C. and G. Scellato (2014): "Firm innovation persistence: a fresh look at the frameworks of analysis," *Economics of Innovation and New Technology*, 23, 423–446.

Mansfield, E. (1962): "Entry, Gibrat's Law, Innovation, and the Growth of Firms," *The American Economic Review*, 52, 1023–1051.

Mowery, D. C. (1983): "Economic Theory and Government Technology Policy," *Policy Sciences*, 16, 27–43.

Nunes, P. M., Z. Serrasqueiro, and J. Leito (2012): "Is there a linear relationship between R&D intensity and growth? Empirical evidence of non-high-tech vs. high-tech SMEs," *Research Policy*, 41, 36–53.

Raymond, W., P. Mohnen, F. Palm, and S. S. van der Loeff (2010): "Persistence of Innovation in Dutch Manufacturing: Is It Spurious?" *The Review of Economics and Statistics*, 92, 495–504.

Silverman, B. W. (1986): *Density Estimation for Statistics and Data Analysis*, London: Chapman & Hall/CRC.

Triguero, A., D. Corcoles, and M. C. Cuerva (2014): "Measuring the persistence in innovation in Spanish manufacturing firms: empirical evidence using discrete-time duration models," *Economics of Innovation and New Technology*, 23, 447–468.