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Persistence of innovation and patterns of firm growth

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Persistence of innovation and patterns of firm growth*

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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

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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 identification of the factors that distinguish and sustain the ability of firms to consistently innovate over time are the subject of a large literature. The empirical studies, as recently emphasized in the review by Le Bas and Scellato (2014), reflect the different theoretical framework offering alternative explanations for the emergence 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 further innovate (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 to be expected between the ability to persistently engage into innovate activities and efforts, on the one hand, and the other dimensions of firm structure and performance on the other ? No matter the preferred explanation for the emergence of innovation persistence, the theoretical frameworks dealing with innovation persistence share that persistent innovators enjoy, by their very nature, superior capabilities than other firms to seizing economic benefits from their constant innovation efforts. Thus, implicitly or explicitly, theories agree that persistent innovators are expected to be comparatively more productive, more profitable and to grow more. However, against this view play the theories emphasizing the uncertainty of the innovation process and the unpredictability of firm growth. This make make it difficult to draw sharp a-priori theoretical conclusions.

On the empirical side, a well established and still developing literature looks at the innovation-growth nexus, recently emphasizing the relevance of innovation for growth trajectories of high-growth firms in the top quantiles of the firm growth rates distribution. Yet, the links between firm growth patterns and *persistence* of innovation remain largely underexplored. To our knowledge at least, the issue is tackled indirectly only in two published articles. Demirel and Mazzucato (2012) analyse the US quoted pharmaceutical firms over the period 1950-2008 and 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 pose two key research questions about the growth trajectories of persistent innovators, asking whether persistent innovators grow more than other firms, and whether innovation persistence affects persistence of growth itself. While the former question is partly addressed in the scant literature mentioned above, we do not know of previous attempts tackling the relation between persistence of innovation and persistence of growth. Indeed, there is evidence, offered by studies searching for the drivers of firm growth persistence, that innovation (similarly to other firm characteristics) provides little explanatory power on persistence of growth, in agreement with theories of firm growth as essentially resulting from mere luck. We test whether persistence in innovation, rather than innovation *per se*, turns out as distinctive feature of firms that are able to persistently grow over time.

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 cases, distinguish between persistent and occasional innovators based on innovation surveys (such as the European CIS). But the rotating nature of the surveyed 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). 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. Thus, we first explain how we exploit the data in the identification of persistent innovators. Next, we introduce the research questions, the related working hypothesis 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

The innovation studies offer a number of different approaches to the identification and measurement of persistence in the innovative activity of firms. Traditionally, most studies are primarily concerned with understanding to what extent persistence is indeed an inherent feature of innovation processes of firms, taking different proxies such as R&D, or patents, or other. Different notions of persistence are used corresponding to different empirical models, in terms of, e.g., length of innovation spells, degree of autocorrelation or properties of transition matrices. These approaches deliver a quite rich empirical picture on the "average" degree of persistence in a given sample of firms, and also helps dissecting the factors (firm characteristics or external to the firms) that favor or hinder innovation persistence. However, these studies do not provide an operational definition of persistent innovators.

Our study here is more closely related to a relatively smaller set of studies that starts from an a-priori definition of persistent innovators. The common approach is to define as persistent innovators those firms that repeatedly perform a given innovation activity over time. 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 that 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 a more reliable test bed. Further complications arise even with consistent panel datasets, however. First, the very notion of innovation persistence that one can measure, and the results of the analysis, sensibly vary with 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 qualify as persistent innovators if we look over relatively shorter time horizons (Le Bas and Scellato, 2014). Second, from previous studies we also know that different innovation activities feature heterogeneities in their likelihood to be repeatedly undertaken over time, and not necessarily due to an explicit decision of a firm to innovate sporadically or continuously innovate over time, but rather due to the inherent specificity of the various innovation activities. For instance, R&D represents a "weak" measure of innovative persistence, since some R&D expenditures are very likely to be repeatedly recorded over time by many firms that happen to perform some R&D in at least one year. Conversely, filing for patents or introducing new products are considered as "strong" measures for identification of innovation persistence, due to inherently more complex processes underlying these two innovation activities. The existing evidence supports 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 if the aim is not merely to identify a group of persistent innovators, but to explore either the determinants or the effects of innovation 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 firm 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. Open choices concern how many years can be considered enough to qualify a firm as persistently innovative, and whether one should restrict the group of persistent innovators to only include firms innovating in consecutive years, or rather 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.

Finally, 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 innovation persistence is evaluated according to different innovation dimensions.

2.2 Regression models, hypothesis 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), also taking into account the different dimensions of innovation.

Our first research question pertains to the potential superior growth performance of persistent innovators vis a vis other firms. We specify 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 (R&D expenditure, product or process innovation, and patenting). 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.

We expect different innovation dimensions to heterogeneously impact firm growth. The ability of firms to persistently generate innovative outputs (new products or new patents) is expected to be more relevant for firm growth, as opposed to persistent R&D or process innovation, due to the closer association between the former types of innovation activities and growth due to "innovation-driven" market success. Indeed, the intrinsic uncertainty characterizing R&D activities – i.e. the uncertainty concerning the probability that R&D translates in economically successful innovation as well as the uncertainty regarding the time needed for such effects to spread out – makes the relationship between R&D and firm growth relatively more nuanced. On similar grounds, firms performing process innovation persistently are not necessarily expected to perform better than other firms in terms of growth. In fact, persistence in process innovation could signal, on the one hand, a strong price competition to which firms react by constantly seeking to introduce efficiency within the production process. On the other, restructuring of processes is more likely to happen in periods of crisis and uncertain prospects for the firm, thus accompanied by shrinking sales or very slow growth. Overall, our working hypothesis is that a positive "growth premium" for persistent innovators is more likely in the case of persistent product innovators or persistent patenting firms, rather than for firms that persistently perform R&D or process innovation.

The second research question we address is whether 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

$$G_{it} = \alpha_0 + \alpha_1\, G_{it-1} + \alpha_2\, Pers_i + \alpha_3\, G_{it-1} \times Pers_i + \alpha_4\, X_{it-1} + u_{it}\ . \tag{2}$$

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, conditional on firm controls X, 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.

Although we lack of an explicit theory linking persistence of innovation and persistence of growth, the (maybe naive) economic intuition would be that companies persistently engaged in innovating and changing over time should be more apt to create and preserve a strong competitive advantage over time, and thus to display more persistent growth patterns. However, for reasons partly overlapping with the considerations introduced in discussing Equation (1), we expect heterogeneity of results according to the different indicators of innovation persistence. Our main hypothesis is that companies persistently capable of translating their knowledge into marketable innovations are also those more likely to preserve such a superior "competitive character" over time. Thus, we predict firms that continuously introduce new products or new patents to have more chances to enjoy a positive "growth persistence premium", as opposed to firms that persistently perform R&D or process innovation. We must also recall that growth persistence has been repeatedly found to be quite difficult to predict on the basis not only of innovation variables, but more generally with regard to many other proxies of firm characteristics. Such evidence has been interpreted as confirming theories that explain firm growth as stemming essentially from mere luck. Within this view one could envisage an opposite prediction of a zero correlation between innovation persistence and persistence of growth.

In estimating both Equation (1) and Equation (2) we complement simple OLS with quantile regressions (QR) techniques, allowing to explore the variation of coefficient estimates along the conditional distribution of growth rates. This is in line with the recent literature on the links between innovation and firm growth. In fact, beyond a general interest into exploring heterogeneities across growing and shrinking firms, there is increasing recognition that innovation is particularly important for high-growth firms in the top quantiles of the growth rates distribution, whereas the effect of innovation on growth of the "average firm" is often difficult to uncover.[1] Although there is no clear guidance from theory or previous empirical studies, our hypothesis is that persistent innovators are expected to outperform other firms – both regarding growth premia and the ability to grow persistently – along all the quantiles of the growth rates distribution, since the ability to persistently innovate create the conditions for both slow-growing and high-growth firms to outperform other firms in the same quantiles. Of course, quantile regression estimates may also be subject to the above discussed heterogeneities that may be in place between growth patterns and the diverse dimensions of innovative activity that we measure in the different indicators of innovation persistence. We can thus envisage that also when looking at growth quantiles, persistent innovators in product or patents are more likely to grow more and more persistently than other firms in the same quantiles, while persistence in R&D and process innovation can have more indirect, and eventually insignificant effects.

We use standard conditional quantile regression (Koenker and Bassett, 1978), modified to tackle potential endogeneity of the persistent innovator dummies. The overall empirical strategy to divide the sample into two sub-periods already reduces the joint determination between growth and the definition of persistent innovators, since the construction of the $Pers$ dummies does not directly exploit data over the years 2000-2012 considered to analyse the dynamics of growth. Nonetheless, a residual risk of bias might remain, to the extent that observed and unobserved firm characteristics that are responsible for the assignment to the groups of persistent innovators in the first sub-period might be correlated with unobserved determinants of growth in the second period. This might be the case, in practice, if one believes that innovation decisions in the last years of the first sub-period are driven by firms' forecasts of future growth occurring in the initial years of the second sub-period. We address this issue by means of a standard two-steps procedure for a dummy endogenous variable model.

[1]The choice of QR techniques also relates to the abundant evidence (confirmed also in our data, see below) that firm growth rates display fat-tails. QR techniques are, thus, preferred in estimating growth regressions, as they are robust to outliers and non-Gaussian distribution of the error term.

As a preliminary step, we use the data in the first sub-period 1990-1999 to build predicted probabilities to belong to the group of persistent innovators. This is operationalized via a Probit where each 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 intangible assets per employee that we use as exclusion restriction: it 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 the $Pers$ status, as we have defined it, does not vary over time, these first-step Probit models take as regressors the firm-level time-series average of the included covariates. Next, in the second step, the firm-specific fitted probabilities ($P - scores$) obtained from the first-step Probit are 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.[2]

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 with 10 or more employees active in manufacturing, observed over the period from 1990 to 2012. 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 combined 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 were made 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.[3]

[2] The first-step Probit estimates display statistical significant of the regressors and considerably high explanatory power (area under the ROC curve above 0.66). 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. This alternative procedure does not affect the results presented in the rest of the paper. The results of the Probit estimates are all available upon request.

[3] 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)

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 of size essentially implies that we focus on market shares relative to the relevant sector. It also implicitly removes common trends in sales, such as due to prices or demand cycles, affecting all the firms in the same sector. Notice that we implemented basic cleaning of outliers at the bottom and top extreme of growth rates, excluding few firm-year observations (14 equally distributed among persistent innovators and other firms) with $G_{i,t} > 5$ or $G_{i,t} < -5$.

We 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 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 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 want to control for innovation dynamics characterizing the firms over the estimation sub-period. Therefore, we include a measure of R&D intensity, defined as annual R&D expenditures per employee. The relation of the latter with growth is potentially difficult to predict, given uncertainty of R&D outcomes, but previous studies tend to agree that R&D may have a beneficial effect on growth of high-growth firms at least. 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.[4]

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.

[4]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. Anyway, a good deal of sectoral variation is already controlled for by the normalization of size in the definition of annual growth rates.

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

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.

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 thus entering tour empirical analysis over the second half of the sample (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, and a similar share (12%) is found for firms that persistently carry out process innovation. Conversely, persistent product innovators are remarkably less frequent (involving the 3% of firms), and persistence in patenting is an even less spread (only 1% of the firms). The relatively higher frequency of firms being persistent in performing R&D may 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" and thus more often undertaken 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 the patent systems functioning or to firm specific preferences for innovation protection strategies. Overall, our classification of firms in the different persistent innovators categories is well in tune with previous studies' distinction between weak vs. strong measures of innovation persistence.

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

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

different definitions of persistent innovators indeed identify different groups of firms. That is, it is likely that firms found to be persistent innovators with respect to one innovation dimension are not necessarily persistent innovators also along the other innovation activities. Such heterogeneities lend empirical support to the relevance of our choice to compare the growth 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 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.[5] Each graph compares persistent innovators and other firms, according to the different innovation proxies. At a general level,

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

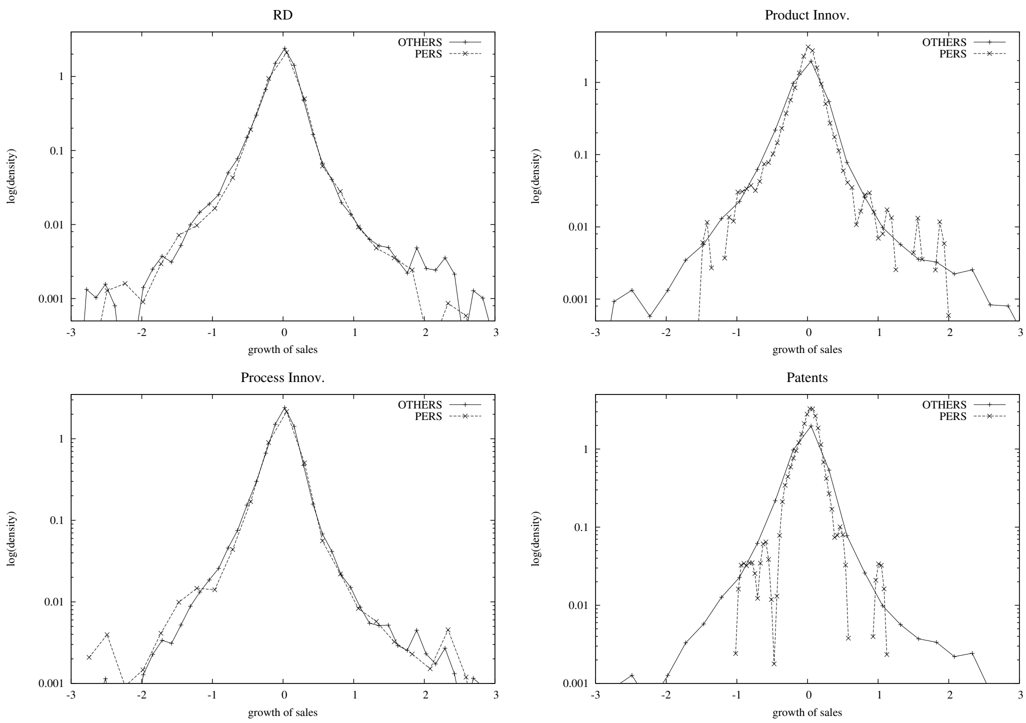

Figure 1: Kernel densities of sales growth as defined in Eq. (3), for persistent innovators (PERS) vs. other firms (OTHERS), by different innovation persistence indicators.

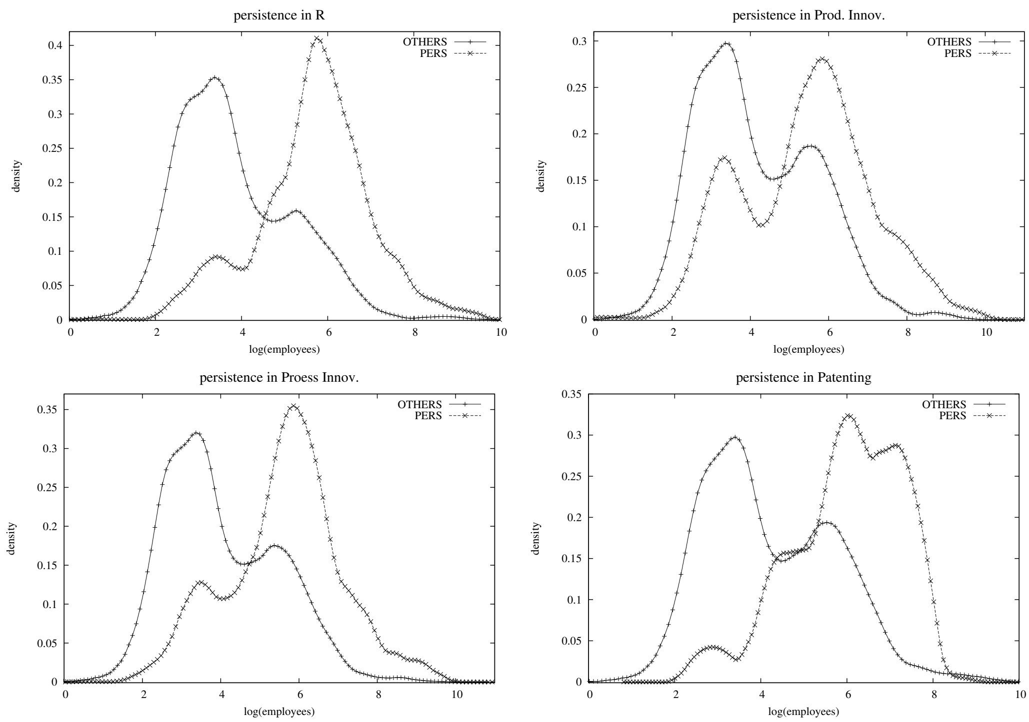

Figure 2: Kernel densities of firm size, as (log) employees, for persistent innovators (PERS) vs. other firms (OTHERS), by different innovation persistence indicators.

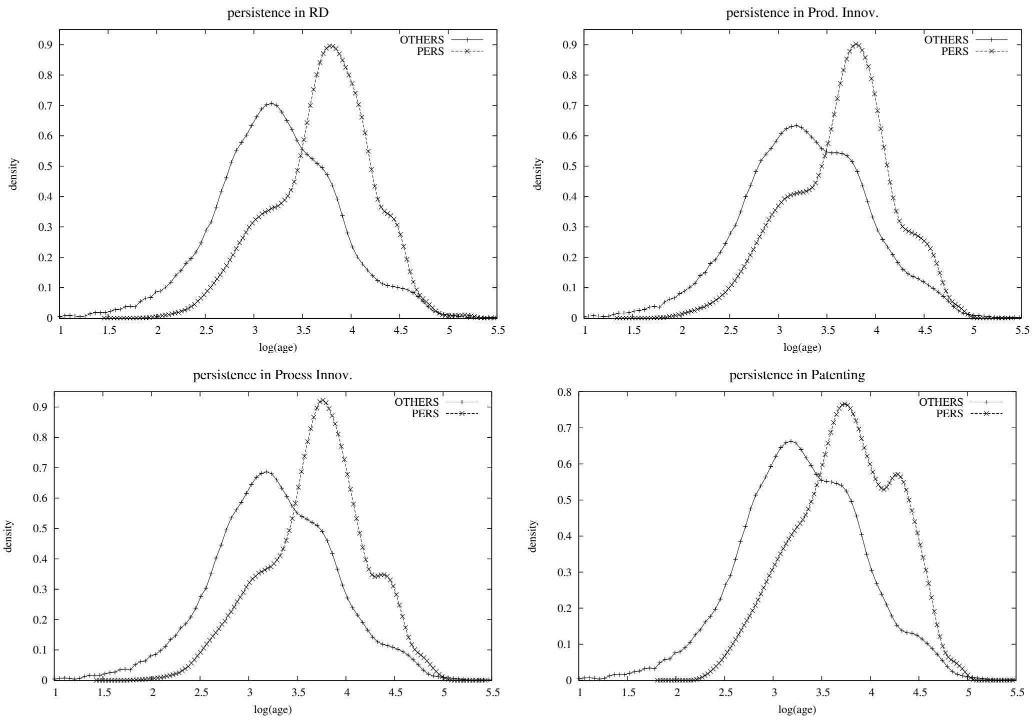

Figure 3: Kernel densities of (log) age, for persistent innovators (PERS) vs. other firms (OTHERS), by different innovation persistence indicators.

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 (but the relatively lower number of firms in this category can play a role in this finding).

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

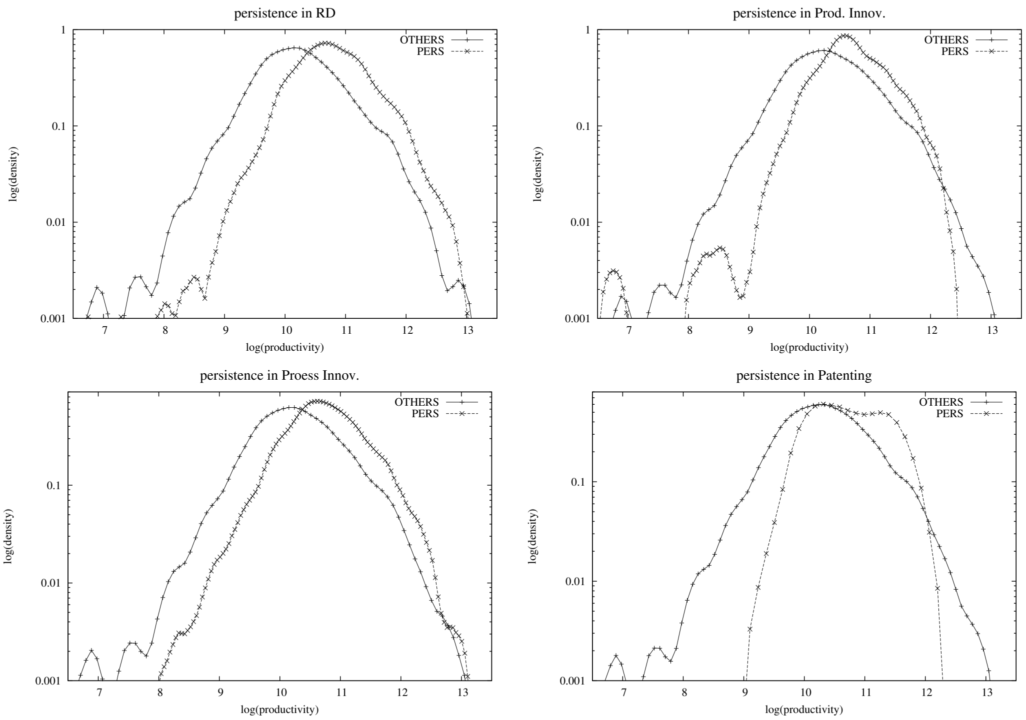

Figure 4: Kernel densities of (log) productivity as real value added per hours worked, for persistent innovators (PERS) vs. other firms (OTHERS), by different innovation persistence indicators.

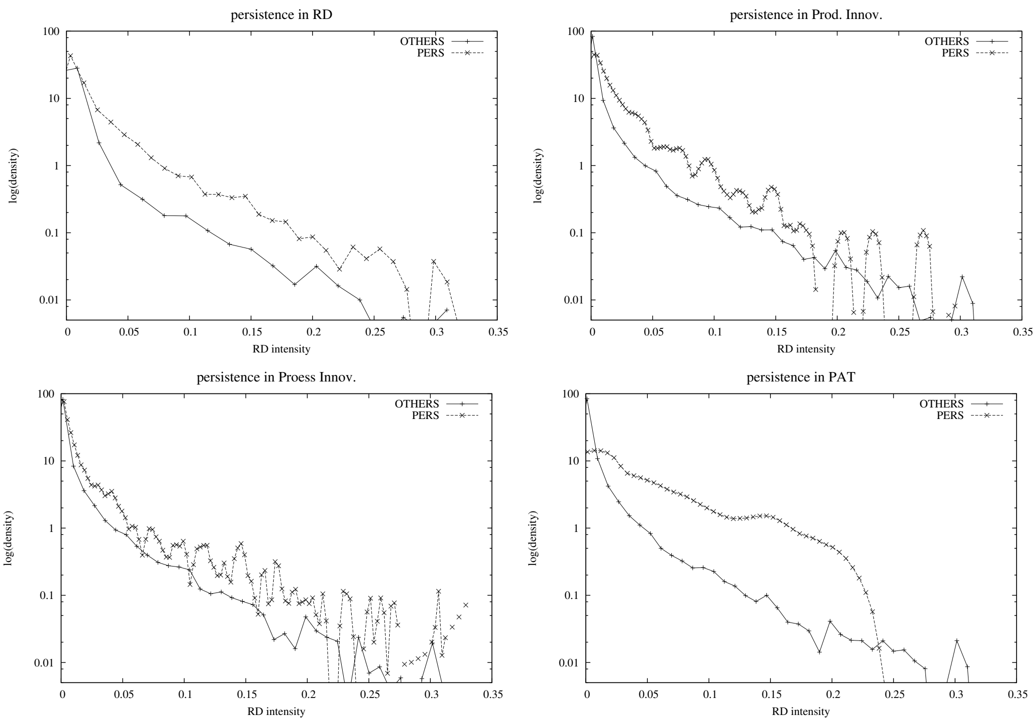

Figure 5: Kernel densities of R&D intensity, as R&D expenses per employee, for persistent innovators (PERS) vs. other firms (OTHERS), by different innovation persistence indicators.

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 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 but higher than growth of other firms in the bottom quantiles, while it is positive, although weaker than growth that of the other firms among high-growth firms in the top quantiles. A simple test of the null "$constant + \beta_1 = 0$" (see last column of the Table) confirms this conclusion.

Of course, these patterns may suffer from a good deal of omitted variable bias and residual simultaneity between growth and $Pers$ dummies. We thus consider as more reliable the estimate of a full specification of regression (1), where we include all the firm-level controls and the P-scores from the first step Probit. Tables 5-8 display the results obtained with the different indicators of innovation persistence. In general, the coefficients on the $Pers$ dummies reveal significant heterogeneities across innovation persistence indicators. First, if we take persistence in R&D (in Table 5), persistent innovators display a negative growth premium along practically the entire distribution of growth rates. Second, for the other innovation persistence indicators we find largely insignificant differences in growth performance: in basically all the quantiles, persistent product innovators (in Table 6), persistent process innovators (in Table 7), and persistent patenting firms do not differ from other firms in the same conditional quantile. However, complementing the generalized low significance of the coefficients on the $Pers$ dummies, persistent process innovators and persistent patenting firms display comparatively lower growth rates 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 when we take R&D to define innovation persistence.

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.

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), conditional on controls, while we are mostly interested in the additional "growth persistence premium" estimated via the coefficient on the interaction term. We focus the comments on these factors.[6]

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. We find that the firms that are not in the group of persistent innovators display positive autocorrelation up to the 6^{th} decile, while anti-correlation emerges among high-growth firms in the top quantiles. However, 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. This pattern is robust across the different measures of innovation persistence. 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, independently from the measures of innovation persistence considered.

The main patterns replicate when we estimate the full models including the firm-level controls, reported in Tables 10-13. Concerning firms that are not persistent innovators, the estimates on G_{t-1} lose some statistical significance in the central quantiles, but we still confirm a (mild) positive autocorrelation of growth in the left part of the growth rates distribution and a (mild) anti-correlation in the top quantiles. Further, 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 tend to replicate the patterns observed in the previous section. 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 along all the growth quantiles.[7]

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

[7]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) considering only the period 2000-2008. 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 distinctive characteristics and the determinants of persistently innovative firms, there is limited empirical effort to verify if it is indeed the case that persistent innovators display peculiar patterns in terms of growth as compared to the other firms populating the economy. The analysis developed in this paper contributes to fill this empirical gap. We ask whether persistent innovators grow more than other firms, and if innovation persistence is associated to higher growth persistence. Previous studies provide (scant) evidence on the former research question, but this study is the first – to our knowledge at least – that jointly analyses innovation persistence and persistence of firm growth.

From a methodological point of view, we exploit a long-in-time panel of Spanish firms allowing for a "genuine" long-run perspective in the identification of growth patterns of persistent innovators, overcoming some limitations of previous analysis of innovation persistence 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. In line with recent trends in the literature on the innovation-growth nexus, we employ quantile regressions techniques to capture heterogeneities along the quantiles of the growth rates distribution, and in particular across slow vs. high-growth firms. Further, we also consider potential heterogeneities in the relation between growth and different types of innovation activities undertaken by firms, comparing growth trajectories across different definitions of persistent innovators, in terms of persistence in R&D, product or process innovation, and patenting.

Existing theories that explain the emergence and the effects of innovation persistence share the common intuition that persistent innovators represent a group of "champions" firms, that are expected to continuously build a capacity to outcompete other firms, both on average and over time. Considering the diverse nature of the innovation activities considered in our analysis, such superior growth performance is expected to be especially strong for firms that persistently engage in innovation activities closer to marketable innovation, such as product innovation and patenting, while the uncertainty of R&D outcomes and the relatively indirect links between growth and process innovation may partly hamper the growth performance of firms persistently performing R&D or process innovation.

Our findings, especially if we control for other relevant firm attributes and residual endogeneity in the definition of persistent innovators, do not support the working hypothesis that persistent innovators should grow more on average and to display higher persistence in their growth dynamics.

First, concerning the differences in average growth between persistent innovators and other firms, we find remarkable heterogeneities across innovation persistence indicators. On the one hand, indeed, 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 process innovators and persistent patenting firms in the top-quantiles of growth, whereas we do not find differences with other firms in practically all the other quantiles. The same lacking difference between persistent innovators and other firms, again along all the quantiles, emerges also if we take persistence in the ability to introduce new products. The result for R&D and process innovation can be explained, as suggested, resorting to the specific nature of these innovation activities: complexity and uncertainty are known to be potentially able to create a wedge between R&D efforts and success on the market, while process innovation often involve restructuring that display more direct effects on cost efficiency, only indirectly passing through growth in the market. More puzzling is the result on the "zero growth premium" for persistent product innovators and persistent patenting firms, that even turns negative for high-growth firms. One interpretation could be that most of the new products and patents introduced by these firms concern non-radical or relatively marginal innovations that do not support an extraordinary growth performance in the following years. Unfortunately, we do not have data (on the specific patents and products) to explore this specific explanation in more details. But, if we just take the results at their face value, the findings agree with that stream of the firm growth literature that underlines the essentially random nature of firm growth, as essentially stemming from chance. Whatever the preferred interpretation, a fair reading of our estimates is that persistent innovators do not certainly grow more, and they may even grow less than other firms.

Our second major finding, once again contrary to the working hypothesis, is that the ability to persistently innovate does not associate with higher persistence in growth rates: 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. In this case, moreover, the results are invariant across all the different indicators of innovation persistence, disconfirming any relevance of the distinction between innovation inputs and output. Also in this case theories of firm growth as stemming from mere luck provide a natural explanatory framework. We add to the previous studies that support the essentially unpredictable nature of firm growth the notion that growth patterns are unstable also for persistent innovators, and that persistence in innovation does not contribute to more persistent growth trajectories.

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