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Persistenco 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 examine the contribution of innovation persistence to shape the long-run dynamics of market expansion of firms. We examine two main research questions. First, do persistent innovators grow more than other firms? Second, do persistent innovators display more persistence than other firms in their growth patterns over time? Exploiting a long-in-time panel of Spanish manufacturing firms over the period 1990-2012, we find a negative answer to both questions: firms that persistently innovate over the first decade, do not grow more and do not display more persistent market share dynamics over the following years. Persistence innovation, therefore, does not warrant to constantly out-compete other firms, both on average and over time. Our results are robust across different definitions of persistent innovators, according to persistence in R&D, product or process innovation, and patenting behaviour. Also, they do not vary by firm size and tend to replicate along the quantiles of the growth rates distribution.

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

In this work we examine the contribution of innovation persistence to shape the long-run dynamics of market expansion of firms.

The innovation-growth nexus has been long investigated. At aggregate level, there is large consensus among scholars that innovation spurs growth, through efficiency gains and knowledge spillovers. Yet, at the micro level, it has been difficult to establish a robust relation between innovative efforts and firm growth, especially in terms of success on the market as measured by dynamics of sales growth and market shares. There is mixed evidence about the effect of innovation on growth of the average firm, while innovation is seemingly more beneficial for growth trajectories of firms in the top quantiles of the growth rates distribution (for a review, see Audretsch et al., 2014). The innovation-growth relation varies depending on the innovation proxy (input vs. output measures, see Bianchini et al., 2018), and by age and size of the firms (Coad et al., 2016). Moreover, innovation does not favor persistence of high-growth (Bianchini et al., 2017).

The absence of strong relations between innovation and market expansion at the firm level can be related to a more general difficulty to identify the structural drivers of firm growth, beyond demographic factors such as age and size, hinting at theories of firm growth as random (Geroski, 2002) or even driven by luck (Barney, 1997). In fact, heterogeneity dominates in the time-profiles of sales dynamics observed across different firms, which appear to some extent as erratic, with mixed evidence on the degree of persistence over time. The inherently uncertain, firm-specific, resource-based, idiosyncratic nature of the innovation processes, all complicate the possibility that innovation can work as robust predictor of the widely heterogeneous patterns of firm growth.

In this study we take advantage of a long-in time panel of Spanish manufacturing firms covering the years 1990-2012 to provide a two-fold shift of focus compared to previous studies. On the one hand, we explore whether it is persistence of innovation, rather than innovation "per se", that matters for sales growth and market share dynamics. On the other hand, differently from most existing studies, we frame the analysis in a long-run perspective. We exploit the first decade of the data (years 1990-1999) to identify persistent innovators, and then examine whether their growth dynamics differ from growth patterns of other firms over the subsequent years (2000-2012) available in the data.

We examine two main research questions relating persistence of innovation to subsequent growth patterns. First, do persistent innovators grow more than other firms, such that we can identify a positive "growth premium" attached to innovation persistence? Second, do persistent innovators display more persistence than other firms in their growth patterns over time, such that we can identify a "growth persistence premium" attached to innovation persistence?

Several theoretical approaches explain the emergence of persistent innovators and how innovation persistence could be relevant for growth patterns of firms, industries and countries (see Le Bas and Scellato, 2014; Raymond et al., 2010, and works cited therein). Innovation persistence is generally expected to be beneficial to growth in endogenous growth models and models of industry dynamics, even from different theoretical traditions. However, random and luck theories of firm growth, as well as the above-mentioned irreducible heterogeneities characterising growth patterns, cast doubts that innovation persistence –much like innovation – may strongly contribute to growth.

Against these possibly contrasting predictions, empirical studies addressing the links between persistence of innovation and patterns of sales expansions are extremely scarce. Demirel and Mazzucato (2012) take a long-run perspective similar to our study, analyzing US listed pharmaceutical firms over the period 1950-2008. They show that persistence in patenting works as a requisite condition in order for R&D to positively impact 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. Brenner and Schimke (2015) ask the question whether innovation has an influence on firm growth persistence. In a panel of German firms, they find that R&D helps both in engendering persistently positive growth and in avoiding persistently declining growth patterns, while engaging in innovative investment projects do not have the same beneficial effects. The results hold for growth of employment, however. We focus on growth on the market, in terms of sales, and emphasize persistence of innovation, rather than the intensity of the innovative efforts "per se".

Our study contributes to this limited empirical literature in a number of ways.

First, the two research questions we pose have not been previously addressed together in the same study. In particular, while there is some evidence that persistent innovators may grow more than other firms, we do not know of previous attempts to investigate the relation between persistence of innovation and persistence of growth.

Second, our empirical strategy to measure innovation persistence and growth dynamics over two non-overlapping time periods, tackles the joint determination between our outcome variables – i.e., success on the market and persistent market expansions – and innovation persistence. Success on the market, in fact, represent an obvious source of those financial resources that may enable firms to persistently innovate over time. The implicit reverse causality is very difficult to break empirically when growth trajectories and innovation persistence are contemporaneously measured over the same years.

Third, and related, by having at our disposal – within our empirical set-up – a relatively long-in-time period of 10 years (1990-99) for the identification of persistent innovators, we can tackle some difficulties in measuring innovation persistence affecting previous studies. Indeed, measuring innovation persistence, by definition, requires to follow firms' innovation decisions consecutively over a relatively long time horizon. Most of the existing studies, by relying upon innovation surveys (such as the European CIS), have only partial information on these patterns. The release in waves every 2-to-4 years, usually without any information on firms' innovation behaviour between two consecutive survey waves, and the changing nature of the survey samples across waves, represent structural limitations affecting the accuracy and reliability of the identification of innovation persistence (Raymond et al., 2010).

Fourth, we account for the potentially heterogeneous relations that may be in place between different types of innovation activity and the dynamics of sales growth. Indeed, we identify four groups of persistent innovators, according to persistence in performing R&D, in introducing product or process innovations, and in filing for new patents. By examining our research questions separately on each group of persistent innovators, we shed light on whether the effects of innovation persistence on growth trajectories vary with the type of persistent innovative efforts undertaken by firms.

2 Background and hypotheses

Our work builds upon a large body of theoretical and empirical contributions studying: (i) firm growth and its determinants, in particular regarding growth on the market in terms of sales and market shares; (ii) the nexus between growth on the market and innovation; and (iii) the emergence and consequences for firm performance of innovation persistence. In this section, we revise some key elements of these literatures and use them to derive working hypotheses about the key research question we ask in this study.

More comprehensive reviews are presented, respectively, in the book by Coad (2009) on firm growth, in the article by Audretsch et al. (2014) introducing a recent special issue of *Industrial and Corporate Change* on firm growth and innovation, and in the introduction by Le Bas and Scellato (2014) to an issue of *Economics of Innovation and New Technologies* specifically devoted to innovation persistence. We draw extensively from these works, but more references can be found therein.[1]

2.1 Firm growth and innovation

Taking an aggregate, economy-wide or industry-level perspective, there is a vast consensus that innovation is an engine of growth. This view, originating in the classical contributions by Schumpeter, gets reflected into theoretical models from different traditions, from the genuinely Schumpeterian evolutionary models inspired to Nelson and Winter (1982), to the neo-classical interpretations of Schumpeterian dynamics in Aghion and Howitt (1992) and Aghion et al. (2005), as well as in endogenous growth models started as in Romer (1986, 1990).

The empirical studies that take this issue at the firm-level, provide a much more nuanced picture. In fact, while some empirical evidence seems to confirm that innovative firms outperform their non-innovative counterparts across a variety of dimensions (including, profits, productivity, and export performance – see Cohen, 2010, for a survey), it has been hard to document a strong positive relation between innovation and dynamics of sales and market shares (Coad 2009; Audretsch et al. 2014). This has been the case, in particular, when looking at the effect of innovation on growth of the "average firm". Classical studies (Scherer, 1965; Mansfield,

[1] We abstract from the mechanisms linking innovation to firm *employment* growth, which are at the core of a parallel, long-lasting literature on the labour-saving vs. labour-augmenting effects of innovation (for exhaustive surveys, see Vivarelli, 2014; Calvino and Virgillito, 2017).

1962; Mowery, 1983) provide support for the hypothesis, but a number of more recent studies, usually covering more representative panel datasets, offer only mixed results (Geroski et al., 1997; Geroski, 2002; Bottazzi et al., 2001; Coad and Rao, 2008). Another recent strand of literature, motivated by the ubiquitous fat-tail behavior of growth rates distributions (Bottazzi and Secchi, 2006), investigate the effect of innovation activities through quantile regression estimates, going beyond the effect on the average firm. In general, these studies show that innovation is indeed beneficial for the growth performance of 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 are sensitive to the specific proxy of innovation used, and some innovative activities do not show a strong positive relation not even with high-growth events (Bianchini et al., 2018).

Several explanations can be offered to account for these contrasting empirical findings.

On the one hand, one can establish link with the more general result that firm-specific, structural determinants of sales growth, beyond simple demographic attributes like size and age, have proven to be hardly identifiable from an empirical standpoint. In this sense, the absence of strong positive links between innovation and growth of output echoes the notion that the patterns of firm growth in the market are largely unpredictable or even guided mostly by luck (Barney, 1997; Geroski, 2002).

On the other hand, the effects of innovation on firm performance, in general, and on growth on the market, in particular, may be blurred by the inherent features of innovation dynamics. The whole Schumpeterian and evolutionary analysis of innovation and industrial dynamics highlights that innovation processes, by their very nature, involve high levels of uncertainty, idiosyncrasy and risk taking, as firms proceed often by trial and error, experiment and test (Nelson and Winter, 1982; Dosi, 1988; Nelson and Winter, 2002; Dosi and Nelson, 2010). Persistent heterogeneity of outcomes is the rule, as emerging from the combination of learning and selection processes, differently shaping innovation and imitation patterns along evolving technological paradigms and trajectories, within different regimes of creative accumulation and creative destruction (Dosi et al., 1995; Malerba, 2007).

The strength of the growth-innovation nexus also varies depending on the type of innovation activity that firms undertake. As stressed in the Knowledge Production Function approach (Griliches, 1979, 1995; Crepon et al., 1998), innovation inputs vs. innovation outputs have heterogeneous relations with firm performance, primarily with productivity, but also with sales and market shares dynamics (Goedhuys and Veugelers, 2012; Bianchini et al., 2018). Among the four dimensions of innovation that we examine in this work, R&D and process innovation are expected to have potentially weaker effects as compared to product innovation and patents. Investing in R&D certainly plays a crucial role in the overall innovation process, as it helps accumulating knowledge, refining or changing products and processes to meet customer needs, and it increases absorptive capacity. However, the relation between R&D and the ability to grow in the market is strongly mediated by the uncertainties of R&D – i.e. regarding the probability that R&D translates in economically successful innovations and products, as well as regarding the time-lags needed for such innovations to spread out and engender new sales and growth in the market. Similarly, process innovation is also predicted to have relatively weak impact on sales growth, according to the classical interpretation that new processes are implemented primarily to reduce costs. Thus, process innovation can sustain expansion of output and sales only to the extent that efficiency and price competition are the main drivers of market share reallocation across firms. That this is the case, however, is called into question by recent empirical evidence on competitive selection dynamics (see Bottazzi et al., 2010; Dosi et al., 2015).

Product innovation as well as patents, are generally regarded as having a stronger, positive link with sales growth. After all, the very commercialization of new products obviously provide firms with the more direct means to achieve growth in the market (Hay and Kamshad, 1994; Cohen, 2010). There may be counter-acting factors, however. Patents are known to imprecisely measure the ability to come up with new inventions or products with commercial value: they are nowadays increasingly used for strategic reasons, not necessarily related to whether a firm is actually at the stage to effectively sell new products or technologies in the market, and growing out of that. Moreover, the introduction of new products may actually "cannibalize" part of the sales growth coming from the existing product portfolio. And the "quality" of products also matters, as we generally expect stronger market expansion in case of more "radical" product innovations, as captured in innovation survey by products new to the market, compared to more incremental improvement, measured as new solely to the firm.

2.2 Persistence of innovation

The innovation literature offers a number of alternative theoretical frameworks to explain the emergence of innovation persistence. 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. The degree of persistence may vary according to different technological regimes, however. According to the classical distinction between Schumpeter Mark I and Mark II regimes (Malerba and Orsenigo, 1995, 1996; Castellacci, 2007), more persistence is expected along phases of creative accumulation, while more disruption characterizes processes of creative destruction. Other studies, not unrelatedly, stress more the knowledge accumulation hypothesis (Geroski et al., 1997; Duguet and Monjon, 2004; Le Bas and Latham, 2009), according to which innovation persistence is due to Arrow's type learning-by-doing effects, to the cumulative and incremental nature of innovation as well as to the emergence of dynamic capabilities. These processes stem, more generally, from the notion of technological trajectories and paradigms developed in the evolutionary theory (Nelson and Winter, 1982; Dosi, 1982). In a related framework, the success-breeds-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 Orsenigo, 2001; Cefis, 2003; Cefis and Ciccarelli, 2005). A further explanation of innovation persistence refers to the sunk costs of performing specific innovation investment, implying that firms get stuck into a certain technological regime. Thus, path-dependent and persistent innovation patterns emerge due to firms developing technological competitiveness strategies based on past knowledge accumulation and internal capabilities (Antonelli et al., 2013).

The empirical literature on the identification and characteristics of innovation persistence, as well documented in the review by Le Bas and Scellato (2014), provide quite heterogeneous results. One source of heterogeneity comes from the length of the time span available in the data. In fact, more firms are able to repeatedly engage in a given innovative activity, and thus qualify as persistent innovators, over a relatively short period of time. But the numbers decrease as the time horizon increases: much less firms are observed to perform innovative activities consecutively over longer time periods.

Another established stylised fact, relevant to our purposes, is that innovation persistence varies according to the type of innovation activity considered. Indeed, different activities feature heterogeneities in their likelihood to be repeatedly undertaken over time. R&D and process innovation represents so-called "weak measures" of innovation persistence: relatively larger shares of innovative firms are observed to repeatedly engage in these type of activities, and it is very common that a firm performing either of these activities in one year, then performs the same activity also over subsequent years. Conversely, filing for patents or introducing new products are regarded as "'strong measures" of innovation persistence. These activities are less frequently observed, due to the inherently more complex processes underlying these two proxies of innovation outputs, making them more lumpy and more rarely repeated over time than R&D and process innovations. The evidence from the literature is that the stronger the measure of innovation behavior considered, and the shorter the time span over which firms are usually able to innovate consecutively over time.

More generally, the empirical literature documents that innovation persistence differs in place, time periods, industries, and according to technological regimes. Of course, this general finding implies that persistence of innovation is strongly likely to vary depending on the specific characteristics of firms. These results suggest the need to consider various controls in estimating the possible impacts of innovation persistence on firm performance.

2.3 Hypotheses

What are, then, the relations to be expected between the ability to persistently engage into innovative activities, on the one hand, and the patterns of long-run growth we study in our empirical analysis ? Once we identify persistent innovators over the first 10 years of data (1990-1999), how do we expect their subsequent growth dynamics to compare against the patterns of other firms, in terms of average growth performance and degree of persistence ?

The theoretical frameworks mentioned above on the emergence of innovation persistence, all share the notion that persistent innovators enjoy superior capabilities than other firms in seizing economic benefits, almost by definition, due to their constant engagement in innovation efforts. Not all innovation activities always yield positive and immediate growth of sales. But the continuous accumulation of knowledge trough persistent R&D, the increased experience with successfully completing the steps leading to marketable or patentable products or ideas, as well as continuously adopting innovative processes, are all seen as beneficial characteristics that make persistent innovators more apt to compete and succeed in the market. Implicitly or explicitly, persistent innovators are predicted to be comparatively more productive, more profitable and, thus, to grow more.

As a result, despite uncertainty, complexity and firm-specific idiosyncratic features of the innovation process may cloud the relation between innovation and sales growth dynamics, we put forward the following

Hypothesis 1. The "growth premium" for persistent innovators is positive: firms identified as persistent innovators in the first 10 years of the data are expected, on average, to grow more than other firms in the following years.

Along similar lines, theories of innovation persistence all share the implicit notion that, exactly by continuously engaging in innovation and technical change, persistent innovators are more likely to self-sustain their strong competitive advantage over time. Thus, they should be more likely than other firms to also repeat a positive sales growth performance over time. On this point, we have little guidance from the empirical literature. There is some evidence (Brenner and Schimke, 2015) that innovation – in general, not innovation persistence specifically – increases persistence of *employment* growth, not only trough sustaining positive growth, but also reducing the likelihood that negative growth events repeat themselves over time. It would not be too extreme to expect similar patterns may also characterize the relation between innovation persistence and persistence of *sales* growth dynamics.

All in all, our working hypothesis on the relation between innovation persistence and persistence of growth states that:

Hypothesis 2. The "growth persistence premium" for persistent innovators is positive: firms identified as persistent innovators in the first 10 years of the data are expected to display, in the following years, more persistent sales growth dynamics than the other firms.

While the above predictions find support from a general reading of the literature, we also consider that different innovation activities may have heterogeneous relations with sales growth and market share dynamics. As mentioned, R&D and process innovation have theoretically weaker, more indirect links with sales expansion than patents and product innovation. We make the assumption that the same ranking holds also when considering persistence in the different innovation activities.

Indeed, the uncertainties characterizing R&D outcomes – hampering strong and immediate translation of new knowledge accumulated through R&D into new discoveries, new products and new revenues – make the relation between persistence in R&D and firm growth relatively nuanced. Persistence in process innovation could signal, on the other hand, an environment characterized by strong price competition to which firms react by constantly seeking to introduce efficiency within the production process, not necessarily leading to higher growth.

Moreover, persistent process innovation is more likely to occur in times of restructuring and/or uncertain prospects for the firm, usually accompanied by no or relatively slow sales growth performance.

Firms that continuously invest in R&D or in process innovation may well have more chances to grow than firms that only sporadically perform some R&D activity or innovate their processes. Still, persistence in R&D and process innovation are both less important for growth than persistently innovating in products or filing for new patents. This leads to a qualification of our first working hypothesis, stating that:

Hypothesis 1a. The expected positive "growth premium" characterising persistent innovators is stronger for persistent product innovators or persistently patenting firms, than for firms that persistently perform R&D or process innovation.

On similar grounds, also when looking at our second hypothesis, we may foresee a certain degree of heterogeneity of effects, depending on the different dimensions of innovation that we consider in defining persistent innovators. Our intuition is that companies persistently able of translating their knowledge into marketable innovations (products or patents) are also those more likely to preserve such a superior "competitive advantage" over time. Thus, we formulate the following:

Hypothesis 2a. Firms that persistently introduce new products or persistently file for new patents enjoy a stronger "growth persistence premium", as opposed to firms that persistently engage in R&D or process innovation.

3 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, starting from 1990 and available to us until 2012. This makes this source particularly suited to follow "long-run" firm dynamics, in turn allowing to evaluate persistence in innovation activities more precisely than in short panels or innovation surveys usually available in the literature.

The ESEE 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 1990, the first survey 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. Since then, in the following years, strong efforts were made to prevent a deterioration of the 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 concerning the strategic dimensions of the firms, but also encompassing standard business register information about balance sheets and profit/loss accounts, together with "CIS-type" questions about innovative strategies and performance. As such, the ESEE dataset provides an extremely large and rich set of variables covering firms' structure and performance.[2]

The data are proprietary, and we accessed through a specific agreement to a subset of the ESEE variables, available to us for all firms over the period 1990-2012.

As the dependent variable in our analysis we measure firm growth in terms of sales. This is computed, for each firm i and year t, as the log-difference

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

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

$$s_{it} = log(S_{it}) - \frac{1}{N}\sum_{i=1}^{n} log(S_{it}) \ . \tag{2}$$

The normalization of size essentially implies that G measures relative sales expansion, and thus the dynamics of success on the market. The normalization, at the same time, implicitly removes common trends in sales, such as due to prices or demand cycles, affecting all the firms in the same sector.[3]

Four variables of the ESEE dataset are available to us to measure different dimensions of the innovative activity of firms: the number of new patents filed during the year (for patents filed either in Spain or abroad); total expenses in R&D during the year; and two dummies indicating whether a firm, in each year, has introduced new products or new processes. The definition of R&D, product innovation and process innovation comply with international standards (according to the Oslo manual).

Available to us is also a set of standard firm characteristics usually employed as control variables in firm growth empirics. We control for age and size, which are well known determinants of firm growth, with young and small-medium firms usually found to grow more. We measure age (labeled as *Age*) from the year of foundation of the firm, and we take the number of employees (*Size*) as the proxy of size to be included as a control variable, since we already measure size in terms of sales in the dependent variable. Further, we include in the analysis a measure of labour productivity (*Productivity*), defined as value added per hour worked, on the theoretical grounds that more productive firms are usually expected to grow more. Lastly, we

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

[3]Notice that we implemented a basic cleaning of outliers at the bottom and top extreme of growth rates, excluding few firm-year observations (6 firm-year observations) with $G_{i,t} > 5$ or $G_{i,t} < -5$.

compute a measure of R&D intensity, defined as annual R&D expenditures per unit of output (*R&D intensity*). The relation of the latter with growth is potentially difficult to predict, given uncertainty of R&D outcomes. We use it as a summary measure of the overall innovative efforts of firms.

4 Persistent innovators

The dictionary meaning of innovation persistence would imply to identify 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 2-4 years, covering in most cases changing samples of firms across the different waves. Persistent innovators in this context are typically identified as those firms that positively answer to survey questions related to innovation activities over two or more consecutive waves. Despite being common, this approach has several limitations. It only applies to the possibly very small set of firms appearing in two or more consecutive 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 over consecutive survey 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 yearly panel data, allowing to follow the same firms consecutively over many years, provides a more reliable test bed. Still, one faces several open choices regarding, first, how many years can be considered enough to qualify a firm as persistently innovative. Second, one needs to decide whether the group of persistent innovators should only encompass firms innovating over the entire time period of observation, or rather to also include firms that innovate consecutively in most years available in the data, but with some year-gaps in between two innovation events. There is clearly a trade-off between a more stringent and more precise definition including only firms that innovate consecutively over a long period of time, and the need to come up with a not too small group of persistent innovators, so to ensure meaningful empirical comparisons with the other firms.

In our empirical setting, by having 10 years of data to identify persistent innovators, different criteria are open to us. Ideally, an arguably unquestionable definition of persistent innovator would be that of a firm that always perform a given innovation activity in all the years over the period 1990-1999. This is not verified in our data, however.

We experimented with less stringent criteria, and eventually define as persistent innovators those firms performing a given innovative activity consecutively for at least 7 out of 10 years in the period 1990-1999. This criterion surely allows to identify firms that do not innovate only

Table 1: Persistent innovators in the sample

	Number of firms	Share
R&D persistence	321	10.1%
Product innovation persistence	100	3.5%
Process innovation persistence	358	11.2%
Patenting persistence	35	1.2%

Notes: Number of persistent innovators, by innovation persistence indicator. Figures computed on non-missing observations for all relevant variables (dependent and controls) over the period 2000-2012. Percentage shares are over the total number of firms (3193) in the data.

occasionally over the considered period. Also, with this criterion we substantially eliminate the possibility of long gaps between two innovation events: the firms identified as persistent innovators may fail to perform a given innovation activity for no more than three years over the period 1990-1999, with all the failures concentrated in either the initial three or in the last three years.

According to the adopted criterion, we build four groups of persistent innovators, by applying the identification strategy to the four innovation activities considered in this work (R&D expenditures, product and process innovation, newly filed patents). Separate analysis of growth trajectories across the four groups serve to test our hypotheses that innovation persistence may have heterogeneous relations with sales growth, depending on the specific innovation activity considered. At the same time, the four categories of innovation persistence account for the heterogeneity across strong vs. weak measures of innovation persistence.

Table 1 reports the number of persistent innovators identified in the data over the first ten years 1990-1999 and that, thus, enter our empirical analysis of growth trajectories over the period 2000-2012, distinguishing by innovation indicator. In line with previous studies, the figures highlight that persistent innovators represent a relatively small cluster. Over the 3193 firms that we can follow over 2000-2012, 321 firms persistently perform R&D (about 10% of the total), and similar figures (358 firms, 11% share) emerge for firms that persistently carry out process innovation. Conversely, persistent product innovators are remarkably less frequent (100 firms, about 3.5% of the total), and persistence in patenting is even more rare (35 firms, a 1% share). This heterogeneity in the frequency of the different persistent innovators categories is well in tune with the evidence on weak vs. strong measures of innovation persistence highlighted in previous studies.

Table 2 reports the pairwise correlations between the four innovation persistence indicators, as a way to appreciate the degree of overlapping between the groups. In general, the correlations are 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 alternative definitions of persistent innovators indeed identify different groups of firms: firms found to be persistent innovators with respect to one innovation dimension are not very likely to be persistent innova-

Table 2: Pairwise correlations 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: Asterisks denote significance at 1% confidence level (Bonferroni adjusted).

tors also along the other innovation activities. Such heterogeneities lend empirical support to the choice to separately analyse the growth trajectories of persistent innovators across different innovation dimensions.[4]

Notice, lastly, that the persistent innovators that we identify over the initial years 1990-1999, continuously innovate also over the period 2000-2012. Indeed, about 70% of them perform some type of innovation activity for 7 or more 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.

5 Descriptive analysis

As a preliminary empirical exercise, we explore the "identity cards" of persistent innovators, providing a descriptive comparison of growth and firm characteristics against other firms over the period 2000-2012.

We first look at kernel estimates of the empirical distribution of the variables across the different groups.[5] In Figure 1 we report (on a log-scale) the kernel densities of relative sales growth rates G across persistent innovators and other firms, according to the different innovation proxies, pooling over time. All the estimates, in all groups, display fat-tails and tent-shaped behaviors, in agreement with previous evidence on the ubiquity of this empirical stylised fact. However, we do not observe any striking difference across persistent innovators and other firms, independently from the innovation dimension involved. The shapes are similar and show a significant degree of overlapping. 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, persistently patenting firms display less dispersed growth rates (but the low number of firms in this category can play a role in this finding).

We find more marked differences when we compare the kernel densities of firm characteristics. Firm size distributions (as number employees), reported in Figure 2, show bimodalities in all groups, but the distributions estimated for persistent innovators tend to lay to the right of

[4]The amount of variance extracted by the first component, in a principal component analysis of the four dummy variables identifying persistent innovators, is 46.17%. This confirms that there are common factors underlying the groups of persistent innovators, but the overlap is not that high.

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

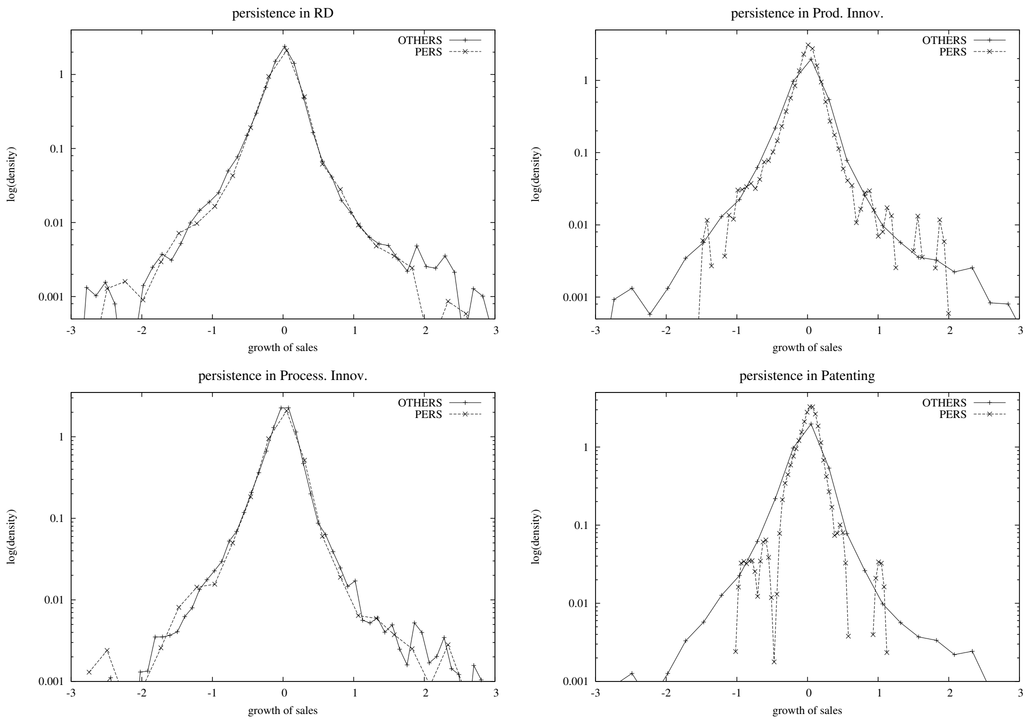

Figure 1: Kernel densities of sales growth G as defined in Eq. (1), for persistent innovators (PERS) vs. other firms (OTHERS), by different innovation persistence indicators.

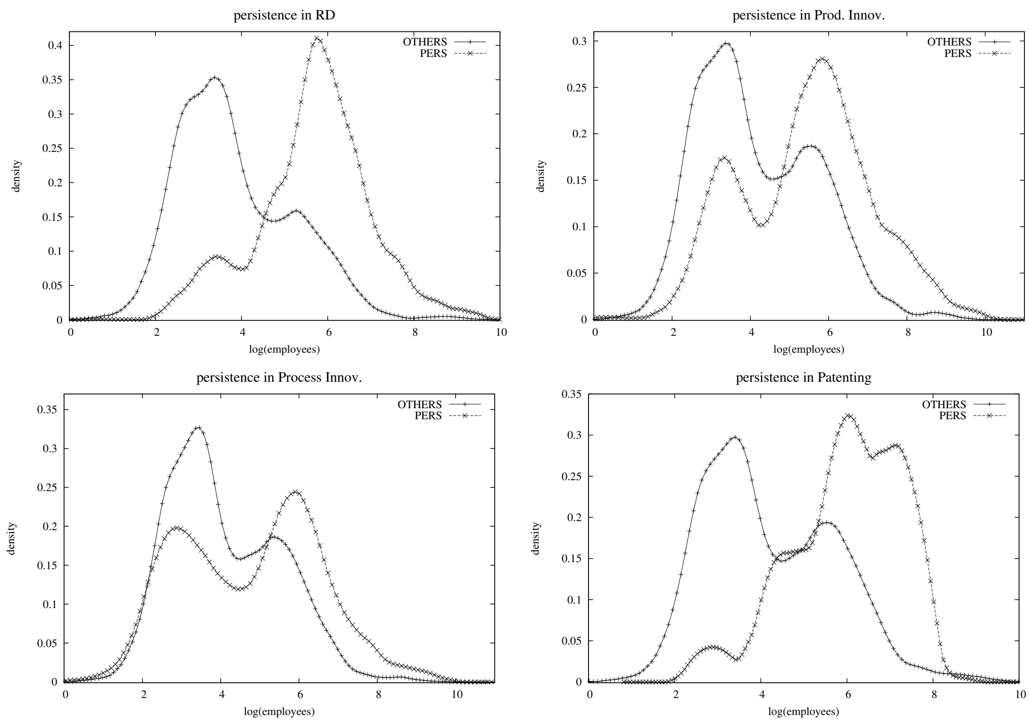

Figure 2: Kernel densities of firm size, as (log) employees, for persistent innovators (PERS) vs. other firms (OTHERS), by different innovation persistence indicators.

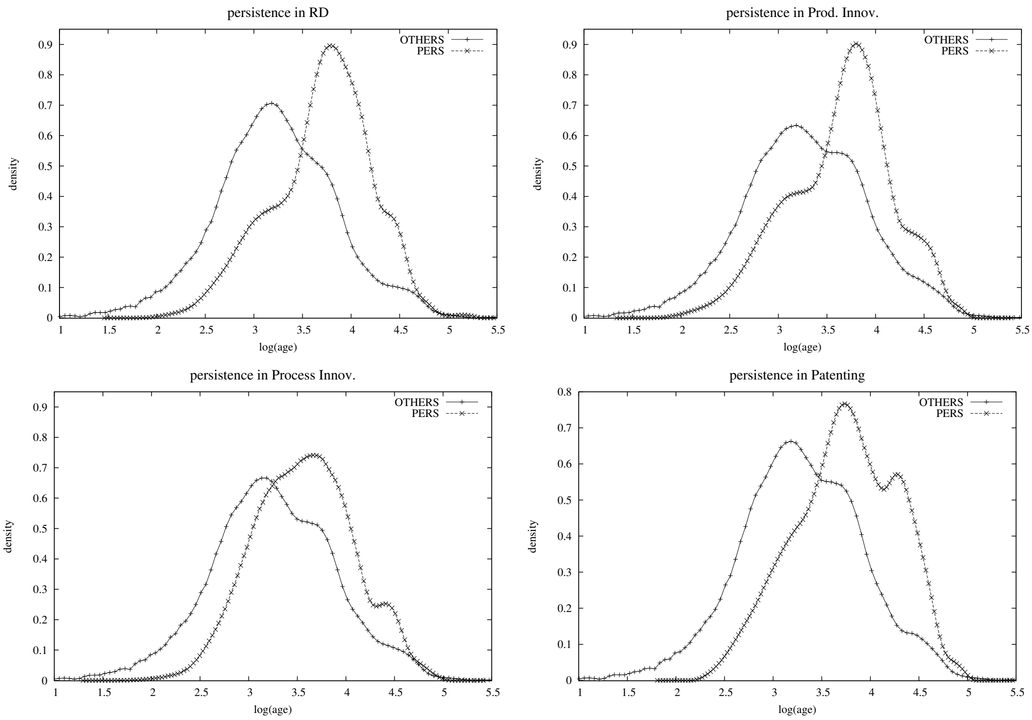

Figure 3: Kernel densities of (log) age, for persistent innovators (PERS) vs. other firms (OTHERS), by different innovation persistence indicators.

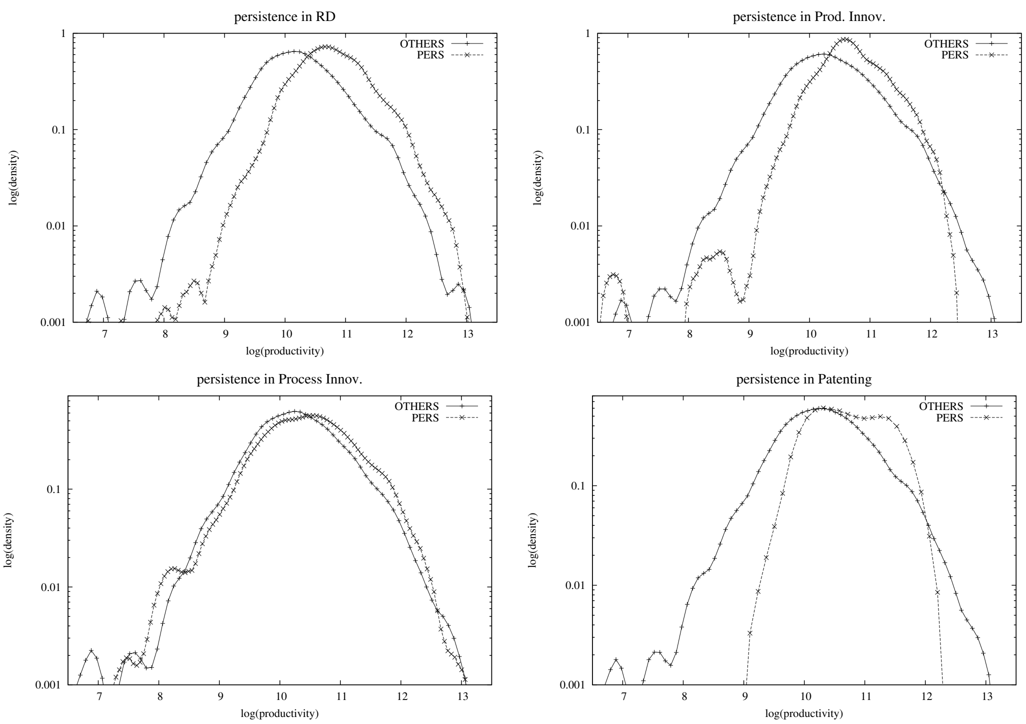

Figure 4: Kernel densities of (log) productivity as real value added per hour worked, for persistent innovators (PERS) vs. other firms (OTHERS), by different innovation persistence indicators.

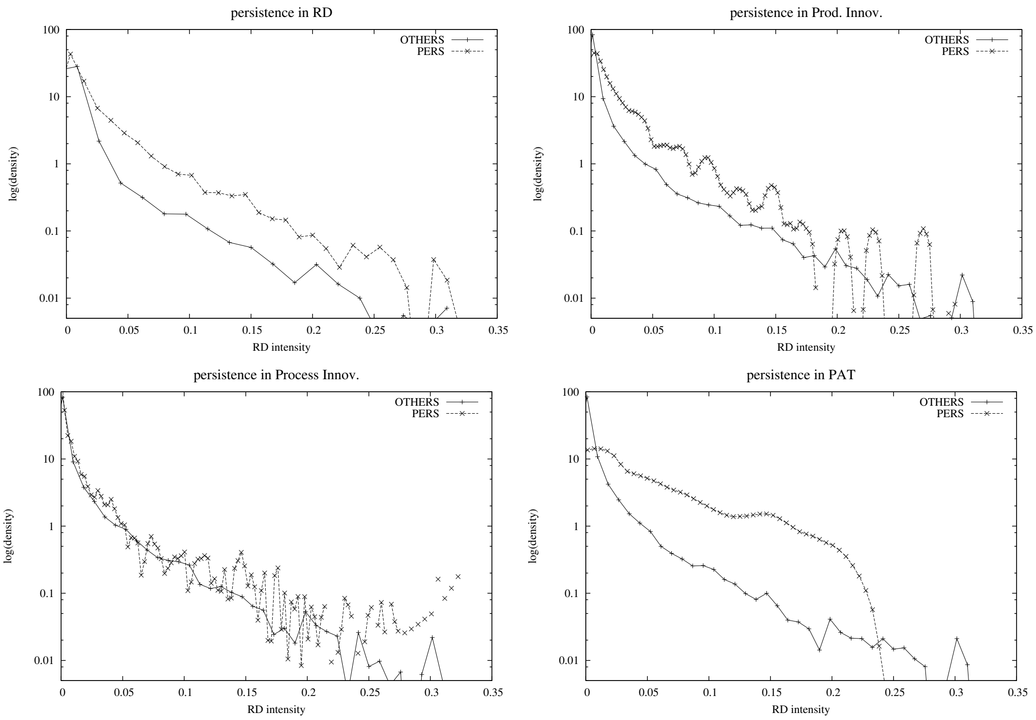

Figure 5: Kernel densities of R&D intensity, as the ratio of R&D expenses over sales, for persistent innovators (PERS) vs. other firms (OTHERS), by different innovation persistence indicators.

the firm size densities estimated for the other firms. Qualitatively similar results, though with less marked bimodalities, emerge for firm age, in Figure 3. The rightward shift of probability mass observed for persistent innovators is even more apparent in this case. Kernel densities of productivity, in Figure 4, display some more overlapping, especially in the central part where most of the mass lies. Also in this case the distribution estimated for persistent innovators tend to have more mass in the right half of the support, compared to the distributions estimated for other firms. Notice however that in the top part of the support, the two groups largely overlap, with persistent innovators less concentrated than other firms in this area (especially for product innovation and patents). Finally, in Figure 5, we find that the densities of R&D intensity estimated for the different types of persistent innovators all tend to dominate, along the entire support.

Another interesting finding is that sales growth and firm characteristics show a considerable degree of heterogeneity (wide supports and fat or long tails) in all groups. Most of the variables considered here are known to be skewed. We add to this known stylised fact the observation that heterogeneity also replicates within the group of persistent innovators: they do not appear as more similar among themselves than other firms do, no matter the innovation proxy involved.

Table 3 shows basic descriptive statistics, again pooling data over time. We report here the median, which is more informative than the mean about central location in case of skewed variables. Figures tend to replicate the patterns emerged from kernel densities. We do not observe striking differences in median growth between persistent innovators – however defined – and other firms, with the exception of persistent patenting firms. Moreover, persistent innovators

Table 3: Descriptive statistics

		Persistent in R&D	**Persistent in Prod. Innov.**	**Persistent in Proc. Innov.**	**Persistent in Patenting**	**Other Firms**
Sales growth	Median	0.0119	0.0119	0.0120	0.0377	0.0111
	Std. Dev.	0.33	0.24	0.36	0.18	0.31
Age	Median	43	41	36	43	27
	Std. Dev.	22	22	21	23	21.75
Size	Median	317	267	142	453	50
	Std. Dev.	1263	1631	1257	677	794
Productivity	Median	10.7	10.6	10.6	10.6	10.3
	Std. Dev.	0.6	0.6	0.7	0.5	0.71
R&D intensity	Median	0.006	0.007	0.001	0.019	0.001
	Std. Dev.	0.24	0.02	0.24	0.04	0.121

Notes: Sales growth as defined in Eq. (1); Age in years; Size is number of employees; Productivity is (log) Euros per hour worked; R&D intensity is R&D expenses over total sales.

are larger and older than other firms, no matter the innovation persistence indicator considered. Conversely, 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 slightly higher for persistently patenting firms and somewhat smaller for persistent process innovators. The standard deviations, much higher than the median in most cases, confirm wide heterogeneities within and across groups.

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

6 Main analysis

We next turn to our main regression analysis, addressing our research hypotheses. To recall, we ask, first, whether firms identified as persistent innovators over the period 1990-99 display more sustained sales growth dynamics than the other firms over the following years 2000-2012. Second, if they exhibit higher persistence than other firms in their sales growth patterns in the same years.

6.1 Persistence of innovation and firm growth

To address our first research question, we specify the following regression equation

$$G_{it} = \beta_0 + \beta_1 \; PERS_i + \beta_2 \; X_{it-1} + u_{it} \quad , \tag{3}$$

where the subscript it stands for the firm-year pair running over the years 2000-2012, G_{it} is firm relative sales growth as defined above, and $PERS_i$ is a dummy assuming value 1 for firms identified as persistent innovators in the years 1990-1999 according to our criterion based on "7-out-of-10" years of consecutive innovation (alternatively measured in terms of R&D, product or process innovation, or filing for patent). Recall that in our empirical set-up, the "innovation persistence status" is time-invariant over the years defining the regression period, hence the omission of the t subscript on the $PERS$ dummy. The set X encompasses all the firm-level characteristics usually included in firm growth regressions and already presented above (age, size, productivity and R&D intensity). These are all lagged to at least partially account for possible simultaneity. The coefficient of primary interest is β_1, capturing the possible "growth premium" for persistent innovators, conditional on covariates.

We experiment with three different estimation strategies. As a benchmark, we first estimate a basic OLS model without controls, where sales growth G is regressed against each different persistent innovator dummy and a constant term, essentially providing a simple OLS difference-in-means test across the groups. Next, we consider OLS estimates of the full specification of regression (3), including all the firm-level controls, plus sector and year fixed effects, thus reducing potential omitted variable bias.

Lastly, we design a simple approach to address potential endogeneity affecting the $PERS$ dummies. This should represent a minor issue, since our overall strategy to divide the sample into two sub-periods is exactly intended to break the simultaneity between growth patterns and the definition of persistent innovators, because the construction of the $PERS$ dummies does not exploit the years considered in the regression analysis. A residual bias may arise, 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 1990-1999, correlate with unobserved determinants of growth in the regression period 2000-2012. 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 through an adaptation to our specific set-up of a standard two-steps procedure to cure a dummy endogenous variable. As a preliminary step, we use the data in the first sub-period 1990-1999 to estimate separate Probit models where each innovation persistence dummy $PERS$ is regressed against the firm-specific time-series averages of the same firm-level controls included in the main regression models (age, size, R&D intensity and productivity), plus intangible assets per employee, which we exploit to ease identification, but we do not include it in the regressions run on the second period. Next, in the second step, the firm-specific fitted probabilities (henceforth, p-scores) obtained from the first-step Probit are added as an additional regressor in an OLS estimate of the main Equation (3) performed on the data over the period 2000-2012.[6]

Table 4 shows the estimation results, distinguishing the analysis by the different indicators of innovation persistence. The estimates deliver a consistent picture: we do not find evidence of a statistically significant difference in the average growth of persistent innovators. The result is robust across the different innovation persistence indicators and also across estimation methods. If anything, the model with controls but excluding p-score correction shows that persistent R&D innovators may even grow less than other firms, conditional on controls. The

[6]In all the first-step Probit estimates, the covariates are strongly significant and all the models show considerably high explanatory power (area under the ROC curve above 0.66). The results are available upon request.

Table 4: Innovation persistence and firm growth - Main Estimates

	R&D PERS			**PROCESS PERS**			**PRODUCT PERS**			**PATENT PERS**		
	OLS	OLS	OLS+PSCORE	OLS	OLS	OLS+PSCORE	OLS	OLS	OLS+PSCORE	OLS	OLS	OLS+PSCORE
PERS dummy	0.00291	-0.0193*	-0.00900	-0.00139	-0.0107	-0.00667	0.00928	0.00536	0.0146	0.0193	-0.0160	-0.00390
	(0.00741)	(0.00840)	(0.00797)	(0.00864)	(0.00619)	(0.00664)	(0.00861)	(0.00938)	(0.0112)	(0.0140)	(0.0109)	(0.0147)
Age		-0.00447	0.00473		-0.00504	0.0169		-0.00686	0.00640		-0.00625	0.0560
		(0.00483)	(0.00640)		(0.00518)	(0.0123)		(0.00424)	(0.00940)		(0.00461)	(0.0291)
Size (lag)		0.0193***	0.0377***		0.0176***	0.0463***		0.0172***	0.0452**		0.0175***	0.0225***
		(0.00212)	(0.00777)		(0.00237)	(0.0136)		(0.00220)	(0.0143)		(0.00207)	(0.00327)
Productivity (lag)		-0.0313***	-0.0379***		-0.0320***	-0.0450***		-0.0322***	-0.0457***		-0.0321***	-0.0539***
		(0.00669)	(0.00831)		(0.00818)	(0.0116)		(0.00633)	(0.0104)		(0.00798)	(0.0144)
R&D intensity (lag)		0.847***	1.109***		0.802***	1.088***		0.795***	1.039***		0.815***	0.999***
		(0.148)	(0.201)		(0.144)	(0.208)		(0.170)	(0.232)		(0.181)	(0.205)
P-score			-0.177**			-0.417*			-0.573*			-1.002**
			(0.0633)			(0.187)			(0.284)			(0.431)
Constant	-0.00695*	0.161*	0.158*	-0.00597*	0.175*	0.197*	-0.00701*	0.181**	0.218**	-0.00667*	0.177*	0.260***
	(0.00312)	(0.0633)	(0.0651)	(0.00293)	(0.0745)	(0.0836)	(0.00284)	(0.0655)	(0.0729)	(0.00265)	(0.0746)	(0.0948)
Observations	12138	11937	11693	12138	11937	11693	12138	11937	11693	12138	11937	11693

Notes: Estimates of Equation (3). Bootstrap standard errors in parenthesis (100 replications). Asterisks denote significance levels: * p<0.05, ** p<0.01, *** p<0.001.

effect is small and only mildly significant, however,in fact turning statistically equal to zero in the model including the p-scores.

Moving to the control variables, the patterns are robust across the different specifications. Age does not display statistically significant association with sales growth. Size and R&D intensity both have a positive association with subsequent growth, whereas the coefficients on lagged productivity are invariably negative. Of course, we are just capturing correlations here, and these variables serve to clean residuals from endogenous component that may bias the coefficient of main interest on the $PERS$ dummy.[7]

6.2 Persistence of innovation and persistence of firm growth

We next address whether persistence in innovation has an effect on persistence of growth itself. In tune with most of the empirical literature on persistence of firm growth, we model persistence in growth rates as an autoregressive process and, thus, specify the following regression equation

$$G_{it} = \alpha_0 + \alpha_1\, G_{it-1} + \alpha_2\, PERS_i + \alpha_3\, G_{it-1} \times PERS_i + \alpha_4\, X_{it-1} + u_{it}\ . \tag{4}$$

This model is a simple extension of Equation (3), where G, $PERS$, X are defined as above, but we add here the 1-year lag of sales growth, G_{it-1}, to capture persistence, and interact it with $PERS_i$ to model the difference in growth persistence associated to the status of persistent innovator. That is, the coefficient α_3 is the coefficient of main interest, and it is identified across firms, yielding an estimate of the average "growth persistence premium" possibly characterizing persistent innovators, conditional on the controls.

We again show three different estimation strategies. First, a benchmark OLS model without controls, where sales growth is regressed against a constant, its lag G_{t-1}, the persistence innovation dummies and the interaction between the two. Next, we estimate via OLS a full-model where we include all the controls (age, size, productivity, R&D intensity), plus sector and year fixed-effects. Lastly, we report OLS estimates obtained after adding the p-scores for persistent innovator status, generated as the fitted values from preliminary first-step Probit estimates as explained above.

The results are presented in Table 5. As before, we perform separate estimates alternatively exploring the growth patterns characterizing the different $PERS$ identified in terms of R&D, product or process innovation and patenting behavior. However, no matter the indicator of innovation persistence considered, we find that persistent innovators do not display any differential persistence in their growth trajectories, as compared to other firms. In fact, the estimated coefficients on the interaction terms are never statistically different from zero, in all models.

Regarding the controls, the estimates tend to replicate the findings of the previous section.

[7] The patterns on the control coefficients observed in these models agree with a preliminary analysis of the pairwise correlations between the controls themselves, and with a preliminary OLS regression between controls and sales growth excluding the PERS dummies (reported in Appendix A).

Table 5: Innovation persistence and persistence of firm growth - Main Estimates

	R&D PERS			**PROCESS PERS**			**PRODUCT PERS**			**PATENT PERS**		
	OLS	OLS	OLS+PSCORE	OLS	OLS	OLS+PSCORE	OLS	OLS	OLS+PSCORE	OLS	OLS	OLS+PSCORE
PERS dummy	0.00347	-0.0209**	-0.00813	0.000162	-0.00876	-0.00339	0.00962	0.00594	0.0157	0.0227	-0.0143	-0.000650
	(0.00839)	(0.00803)	(0.00871)	(0.00831)	(0.00686)	(0.00788)	(0.00960)	(0.0108)	(0.0109)	(0.0157)	(0.0167)	(0.0178)
Sales Growth (lag)	-0.0365	-0.0201	-0.0199	-0.0185	-0.0206	-0.0191	-0.0358	-0.0296	-0.0309	-0.0347	-0.0290	-0.0211
	(0.0265)	(0.0193)	(0.0194)	(0.0225)	(0.0183)	(0.0195)	(0.0299)	(0.0238)	(0.0205)	(0.0298)	(0.0241)	(0.0245)
Interaction	0.00757	-0.0506	-0.0501	-0.0471	-0.0363	-0.0435	0.0550	0.0115	0.0227	0.0402	-0.0806	-0.0756
	(0.0779)	(0.0548)	(0.0620)	(0.0802)	(0.0656)	(0.0602)	(0.0657)	(0.0566)	(0.0619)	(0.155)	(0.158)	(0.148)
Age		-0.00567	0.00819		-0.00669	0.0230		-0.00844	0.00942		-0.00775	0.0649*
		(0.00519)	(0.00798)		(0.00560)	(0.0134)		(0.00476)	(0.00951)		(0.00595)	(0.0280)
Size (lag)		0.0203***	0.0452***		0.0183***	0.0544***		0.0180***	0.0527***		0.0182***	0.0236***
		(0.00264)	(0.00723)		(0.00213)	(0.0137)		(0.00264)	(0.0132)		(0.00228)	(0.00303)
Productivity (lag)		-0.0287***	-0.0374***		-0.0297***	-0.0461***		-0.0297***	-0.0463***		-0.0296***	-0.0543***
		(0.00697)	(0.00789)		(0.00635)	(0.0111)		(0.00730)	(0.0103)		(0.00667)	(0.0124)
R&D intensity (lag)		0.846***	1.202***		0.794***	1.153***		0.787***	1.094***		0.810***	1.005***
		(0.172)	(0.204)		(0.168)	(0.225)		(0.148)	(0.211)		(0.158)	(0.192)
P-score			-0.240***			-0.528**			-0.715**			-1.109**
			(0.0624)			(0.183)			(0.269)			(0.415)
Constant	-0.0158***	0.141*	0.131	-0.0150***	0.158**	0.181*	-0.0157***	0.164*	0.204**	-0.0154***	0.159*	0.245**
	(0.00314)	(0.0682)	(0.0685)	(0.00342)	(0.0555)	(0.0758)	(0.00323)	(0.0667)	(0.0675)	(0.00296)	(0.0651)	(0.0767)
Observations	10554	10447	10246	10554	10447	10246	10554	10447	10246	10554	10447	10246

Notes: Estimates of Equation (4). Bootstrap standard errors in parenthesis (100 replications). Asterisks denote significance levels: * p<0.05, ** p<0.01, *** p<0.001.

Table 6: Innovation persistence and firm growth - 2SLS estimates

	R&D PERS	**PROCESS PERS**	**PRODUCT PERS**	**PATENT PERS**
PERS dummy	-0.123	-0.339	-0.373	-0.160
	(0.0469)	(0.144)	(0.236)	(0.783)
Age	0.00567	0.0373	0.00354	0.00930
	(0.00779)	(0.0211)	(0.00974)	(0.0102)
Size (lag)	0.0305***	0.0279***	0.0257***	0.0322*
	(0.00596)	(0.00616)	(0.00613)	(0.0127)
Productivity (lag)	-0.0281***	-0.0335**	-0.0272**	-0.0326**
	(0.00788)	(0.0102)	(0.00947)	(0.0121)
R&D intensity (lag)	1.117***	0.936***	1.087***	2.408*
	(0.219)	(0.231)	(0.297)	(1.050)
Constant	0.0749	0.0753	0.0912	0.0799
	(0.0807)	(0.108)	(0.100)	(0.0927)
Observations	11693	11693	11681	10107

Notes: 2SLS estimates of Equation (3), with p-scores as instruments for persistent innovation status. Robust standard errors in parenthesis. Asterisks denote significance levels: * $p<0.05$, ** $p<0.01$, *** $p<0.001$.

Conditional on other factors, sales growth tends to positively correlate with lagged size and R&D intensity, while we find negative association with lagged productivity and no statistically significant correlation with age.

6.3 Robustness analysis

The analysis presented so far shows that persistent innovators do not differ from other firms in their subsequent trajectories of sales growth: contrary to our working hypotheses, they do not grow more and do not exhibit more persistence. We inspect the sensitivity of these results to a series of robustness analysis.[8]

A first robustness check is more technical. We exploit exogeneity of p-scores in a different way: instead of adding them to the main equations, we can use them as an instrument for the PERS dummy in Two-Stage Least Squares (2SLS) regression.

Table 6 and Table 7 present the second-stage results, respectively for the two main regressions in Equation (3) and (4), including the full set of controls, plus year and sector fixed-effects. We broadly confirm our main estimates. In general, persistent innovators do not show any "growth premium", and we even find that persistent R&D innovators may actually grow less, on average, than the other firms. Further, as in the main analysis, we find that persistent innovators, irrespective of the innovation indicator, do not grow more persistently.[9]

A second issue we want to address is that in our main analysis of the growth persistence model in Equation (4) we cannot apply standard GMM panel techniques to control for endo-

[8] Anonymous referees provided substantial suggestions along these lines.

[9] Coefficient estimates on the control variables are in line with the main estimates: age is not significant; size and R&D intensity tend to show positive coefficients, while productivity negatively relates with the dependent variable.

Table 7: Innovation persistence and persistence of firm growth - 2SLS estimates

	R&D PERS	**PROCESS PERS**	**PRODUCT PERS**	**PATENT PERS**
PERS dummy	-0.157*	-0.414	-0.423	-0.333
	(0.0539)	(0.168)	(0.275)	(0.958)
Sales Growth (lag)	-0.0281	-0.0328	-0.0359	-0.0328
	(0.0198)	(0.0207)	(0.0220)	(0.0229)
Interaction	-0.0472	-0.00945	0.102	0.644
	(0.0610)	(0.0602)	(0.105)	(0.824)
Age	0.00852	0.0466	0.00449	0.0105
	(0.00913)	(0.0250)	(0.0118)	(0.0122)
Size (lag)	0.0347***	0.0304***	0.0270***	0.0353*
	(0.00665)	(0.00706)	(0.00660)	(0.0147)
Productivity (lag)	-0.0239**	-0.0293*	-0.0235*	-0.0317*
	(0.00806)	(0.0115)	(0.0101)	(0.0132)
R&D intensity (lag)	1.198***	0.971***	1.126***	2.606*
	(0.239)	(0.263)	(0.334)	(1.291)
Constant	0.0199	0.0126	0.0539	0.0552
	(0.0862)	(0.128)	(0.111)	(0.0968)
Observations	10246	10246	10234	8849

Notes: 2SLS estimates of Equation (4), with p-scores as instruments for persistent innovation status. Robust standard errors in parenthesis. Asterisks denote significance levels: * p<0.05, ** p<0.01, *** p<0.001.

geneity of lagged dependent and controls, since the main regressors (the $PERS$ dummies) do not vary over the regression time period 2000-2012. Yet, we can make an attempt to further exploit the panel structure over the years 2000-2012, through a split-sample analysis of the following variation of the baseline model

$$G_{it} = \gamma_0 + \gamma_1 \, G_{it-1} + \gamma_2 \, X_{it-1} + u_{it} \ , \tag{5}$$

estimated separately on the groups of persistent innovators ($PERS = 1$) and other firms ($PERS = 0$), as identified according to the different innovation indicators. In this alternative setting, all the regressors are time-varying, and we can thus apply panel methods, controlling for endogeneity of both lagged growth and covariates. The existence of a "growth persistence premium" for persistent innovators would be revealed by comparing the estimated γ_1 across persistent innovators and other firms. This exercise, moreover, can shed light on two possible explanations why we observed in the main analysis that persistent innovators do not exhibit significantly different growth persistence compared to other firms (recall the insignificant interaction coefficients in Table 5). On the one hand, we could find that both groups do display some autocorrelation in sales growth, but such autocorrelation is statistically equal between the two groups, on average. Alternatively, we could find that both persistent innovators and the other firms show zero autocorrelation in the dynamics of relative growth. Split-sample estimates tell which of the two explanations prevail.

Table 8 reports the findings obtained via a GMM-DIFF estimator, which is more appropri-

Table 8: Innovation persistence and persistence of firm growth - Split sample GMM estimates

	R&D		**PROCESS**		**PRODUCT**		**PATENT**	
	PERS=1	PERS=0	PERS=1	PERS=0	PERS=1	PERS=0	PERS=1	PERS=0
Sales Growth (lag)	-0.0801	-0.134	-0.178*	-0.200*	-0.00316	-0.0365	-0.205	-0.0277
	(0.0590)	(0.177)	(0.0965)	(0.116)	(0.0716)	(0.145)	(0.185)	(0.0307)
Age	-0.00948	-0.118	-0.495	-0.0801	-0.314	-0.195*	-0.990	-0.206
	(0.237)	(0.122)	(0.329)	(0.0924)	(0.266)	(0.0994)	(0.615)	(0.146)
Size (lag)	-0.159	0.130	-0.181	0.0458	-0.0146	0.132	0.285	-0.292
	(0.209)	(0.176)	(0.235)	(0.196)	(0.359)	(0.273)	(0.283)	(0.338)
Productivity (lag)	-0.354*	-0.517***	-0.309**	-0.196**	-0.496***	-0.147	-0.533*	-0.280*
	(0.146)	(0.112)	(0.143)	(0.0830)	(0.134)	(0.125)	(0.236)	(0.103)
R&D intensity (lag)	-0.392	1.043	1.041	-1.634	-0.635	0.277	-0.704	-1.939
	(0.792)	(1.140)	(2.379)	(1.234)	(1.592)	(2.157)	(1.134)	(2.978)
Observations	2025	6886	2017	6894	594	8309	168	8743
IV diagnostics: stat (p-value)								
AR(1) residuals:	-2.91(0.004)	-2.16(0.003)	-2.05(0.040)	-2.81(0.005)	-2.84(0.004)	-3.07(0.002)	-1.84(0.065)	-4.31(0.001)
AR(2) residuals:	-0.78(0.434)	-1.61(0.108)	-1.64(0.102)	-1.68(0.107)	1.02(0.309)	-1.05(0.296)	-0.72(0.473)	-1.61(0.108)
Hansen test:	37.87(0.101)	102.87(0.118)	69.49(0.144)	58.67(0.162)	25.83(0.259)	17.06(0.106)	9.00(0.437)	12.28(0.198)

Notes: Split-sample GMM-DIFF two-step estimates of Equation (5), across persistent innovators (PERS=1) and other firms (PERS=0) as identified by different innovation persistence indicators. Robust standard errors in parenthesis, with small sample correction as in Windmeijer (2005). Asterisks denote significance levels: * p<0.05, ** p<0.01, *** p<0.001.

ate given the relatively low degree of persistence of the dependent variable.[10] When we split the firms according to persistence in R&D, product innovation and patenting, we find that the autocorrelation coefficients are never statistically significant, neither for persistent innovators nor for the rest of the firms. The split-sample estimates based on persistence in process innovation signal negative autocorrelation within both persistent innovators and other firms, but there is no difference in the coefficients estimated in the two groups: point estimates are very close and completely overlap within a 1-standard error confidence band. Thus, we confirm our main finding that growth patterns of persistent innovators do not display more persistence compared to other firms.

Further, we test whether the lack of "growth persistence premium" for persistent innovators is sensitive to the notion of growth persistence that we used in the main analysis. In fact, autocorrelation over time, despite widely adopted in firm growth empirics, just delivers a rather specific definition of persistence. We experiment with a less restrictive notion, by estimating the transition probabilities across the quartiles of the growth rates distribution. This analysis allows us, at the same time, to provide additional evidence: (i) on mobility/persistence in and out different positioning in the overall ranking of relative sales growth, beyond the "average firm" captured in regression models; and (ii) on the degree of mobility/persistence over different time horizons, longer than one year.

Table 9 and Table 10 report, respectively, the 3-years and 5-years transitions across quartiles of the yearly growth distributions computed over all the firms in the period 2000-2012, distinguishing by persistent innovator status and innovation indicators. To ease interpretation of the matrices, we also report two standard measures of intra-distributional mobility. The Shorrocks index considers the degree of persistence on the main diagonal: it takes value 0 if the matrix is the identity matrix (i.e., max persistence, as all firms remain in the initial quartile), and goes to $k/(k-1)$ if the matrix has all zeroes on the diagonal (i.e., full mobility), with k the number of states. In our case, this upper bound is 4/3. The Bartholomew index takes also into account the degree of off-diagonal mobility, assigning higher weights to longer jumps. It takes value 0 if all firms remains in their initial quartile (i.e, max persistence), and it has an upper bound of 1 if all firms makes the longer possible jump compared to their initial quartile (i.e., full mobility).

In general, we find that persistence is relatively low: cells frequencies range in between 20 and 35 percent, which is not that high compared to an hypothetical "fully random" data generating process where all the events (staying in the same quartile and jumping across all the other quartiles) have the same probability (equal to 25%) to realize. The result is rather invariant across persistent innovators and other firms, independently from the indicator of

[10] GMM-SYS uses in general more information, but it can perform poorly when the dependent variable features weak true state dependence, since lagged differences are very weak instruments for the equation in levels. In reported estimates, we use a two-step GMM-DIFF estimator, with the Windmeijer (2005) small sample correction of the standard errors. The instruments set includes various lags of growth, size, productivity and R&D. Age, sector fixed-effects and year fixed-effects are assumed as exogenous, and thus used as instruments for themselves. All specifications pass standard tests for residual autocorrelation and the Hansen test for instruments validity.

Table 9: Transition probabilities across growth quartiles: 3-years transitions

			PERS=1						PERS=0			
R&D		*t+3*	Q1	Q2	Q3	Q4		*t+3*	Q1	Q2	Q3	Q4
	t	Q1	28.09	28.61	21.39	21.91	*t*	Q1	32.25	22.01	20.14	25.61
		Q2	20.88	30.52	27.71	20.88		Q2	23.85	29.91	24.52	21.72
		Q3	20.16	26.42	29.16	24.27		Q3	23.46	28.39	25.79	22.36
		Q4	21.43	23.47	30.87	24.23		Q4	26.01	22.34	23.89	27.75
			Shorrocks =0.960						Shorrocks =0.948			
			Bartholomew =0.376						Bartholomew =0.397			
PROCESS		*t+3*	Q1	Q2	Q3	Q4		*t+3*	Q1	Q2	Q3	Q4
	t	Q1	32.10	27.85	19.89	20.16	*t*	Q1	31.18	22.25	20.54	26.03
		Q2	21.66	31.38	26.92	20.04		Q2	23.59	29.63	24.78	21.99
		Q3	18.42	27.13	31.09	23.37		Q3	24.02	28.15	25.18	22.66
		Q4	22.61	23.62	29.15	24.62		Q4	25.73	22.30	24.31	27.67
			Shorrocks =0.936						Shorrocks =0.954			
			Bartholomew =0.366						Bartholomew =0.400			
PRODUCT		*t+3*	Q1	Q2	Q3	Q4		*t+3*	Q1	Q2	Q3	Q4
	t	Q1	27.52	21.10	30.28	21.10	*t*	Q1	31.63	23.56	19.79	25.01
		Q2	19.74	31.58	32.89	15.79		Q2	23.40	29.90	24.70	21.99
		Q3	18.54	26.49	31.79	23.18		Q3	22.98	28.02	26.18	22.82
		Q4	23.58	21.70	31.13	23.58		Q4	25.20	22.59	24.99	27.22
			Shorrocks =0.952						Shorrocks =0.950			
			Bartholomew =0.370						Bartholomew =0.394			
PATENTS		*t+3*	Q1	Q2	Q3	Q4		*t+3*	Q1	Q2	Q3	Q4
	t	Q1	19.35	32.26	35.48	12.90	*t*	Q1	31.58	23.25	20.14	25.03
		Q2	16.00	32.00	28.00	24.00		Q2	23.20	30.04	25.28	21.48
		Q3	14.00	26.00	28.00	32.00		Q3	22.85	27.94	26.60	22.60
		Q4	9.76	29.27	43.90	17.07		Q4	25.42	22.43	24.89	27.26
			Shorrocks =1.01						Shorrocks =0.948			
			Bartholomew =0.355						Bartholomew =0.393			

Notes: 3-years transitions across quartiles of the yearly growth rates distribution, measured over the period 2000-2012, from the bottom quartile (Q1) to the top quartile (Q4). Results by persistent innovators (PERS=1) and other firms (PERS=0), as identified according to different innovation persistence indicators.

innovation persistence, and it is also robust across the 3-years and the 5-years transitions. Overall, there are some differences across persistent innovators and other firms, but none of the two groups shows a definitely higher growth persistence. In fact, the mobility indexes support this conclusion. The values of the Shorrocks index, mostly around or above 0.95, confirm low persistence in growth patterns, and do not vary much across persistent innovator status, innovation indicator and transition time-length. The same holds for the Bartholomew indexes, all in between 0.3 and 0.4.[11]

[11] We also performed an additional unreported robustness check. Since the global financial crisis and the Great Recession may have played a role, we re-estimated our main regressions in Equation (3) and Equation (4) over a shorter time-period, limited to the years 2000-2008. In all these additional analysis, our main conclusions still apply. The results are available upon request.

Table 10: Transition probabilities across growth quartiles: 5-years transitions

		PERS=1					PERS=0			
R&D	*t+5*	Q1	Q2	Q3	Q4	*t+5*	Q1	Q2	Q3	Q4
t	Q1	26.02	21.19	24.16	28.62	Q1	30.45	23.72	19.90	25.93
	Q2	24.03	32.32	25.14	18.51	Q2	22.62	29.59	26.67	21.11
	Q3	18.44	29.61	29.35	22.60	Q3	20.81	28.06	27.78	23.35
	Q4	20.75	26.42	27.17	25.66	Q4	29.79	24.20	20.90	25.11
		Shorrocks =0.956					Shorrocks =0.957			
		Bartholomew =0.385					Bartholomew =0.403			
PROCESS	*t+5*	Q1	Q2	Q3	Q4	*t+5*	Q1	Q2	Q3	Q4
t	Q1	29.60	24.40	18.80	27.20	Q1	29.49	22.88	21.30	26.33
	Q2	19.48	34.96	25.79	19.77	Q2	24.12	28.77	26.44	20.67
	Q3	17.12	30.16	32.07	20.65	Q3	21.22	27.90	26.88	24.00
	Q4	27.52	24.81	22.87	24.81	Q4	28.14	24.59	21.95	25.32
		Shorrocks =0.923					Shorrocks =0.965			
		Bartholomew =0.382					Bartholomew =0.404			
PRODUCT	*t+5*	Q1	Q2	Q3	Q4	*t+5*	Q1	Q2	Q3	Q4
t	Q1	22.08	24.68	27.27	25.97	Q1	30.02	23.02	20.40	26.56
	Q2	23.85	31.19	28.44	16.51	Q2	22.91	30.21	26.10	20.78
	Q3	20.00	27.62	33.33	19.05	Q3	20.19	28.54	27.79	23.47
	Q4	17.33	25.33	30.67	26.67	Q4	28.67	24.61	21.64	25.08
		Shorrocks =0.956					Shorrocks =0.956			
		Bartholomew =0.370					Bartholomew =0.401			
PATENTS	*t+5*	Q1	Q2	Q3	Q4	*t+5*	Q1	Q2	Q3	Q4
t	Q1	21.74	30.43	26.09	21.74	Q1	29.65	23.05	20.71	26.59
	Q2	17.65	29.41	35.29	17.65	Q2	23.04	30.30	26.17	20.48
	Q3	10.53	34.21	31.58	23.68	Q3	20.44	28.32	28.11	23.14
	Q4	0.00	35.71	32.14	32.14	Q4	28.61	24.40	21.91	25.08
		Shorrocks =0.950					Shorrocks =0.956			
		Bartholomew =0.319					Bartholomew =0.401			

Notes: 5-years transitions across quartiles of the yearly growth rates distribution, measured over the period 2000-2012, from the bottom quartile (Q1) to the top quartile (Q4). Results by persistent innovators (PERS=1) and other firms (PERS=0), as identified according to different innovation persistence indicators.

7 Extended analysis

7.1 The role of firm size

One interesting issue is whether our main results are driven by a firm size effect. Despite the literature on technical change recently started to recognize the role of small firms in innovation persistence (Corradini et al., 2016), most studies have repeatedly stressed that large firms are especially likely to display innovation persistence, somewhat assuming that persistence does not manifest in phases of creative destruction were small firms play a major role. But we also know, from the empirics of firm growth and Gibrat's Law, that larger firms usually display more stable growth paths, characterised by smaller growth jumps than small-medium firms, on average and over time, and generally show a lower cross-sectional dispersion of growth rates.

Table 11: Innovation persistence and firm growth - SMES vs. Large firms

	R&D		**PROCESS**		**PRODUCT**		**PATENT**	
	SMEs	Large	SMEs	Large	SMEs	Large	SMEs	Large
PERS dummy	-0.0133	-0.000662	-0.00108	-0.0143	0.0229	0.00206	-0.00768	0.0348
	(0.0121)	(0.0118)	(0.00846)	(0.00982)	(0.0143)	(0.0149)	(0.0318)	(0.0201)
Age	-0.00178	0.0304	0.00371	0.0617	-0.00148	0.0502	0.0285**	0.116
	(0.00492)	(0.0220)	(0.00700)	(0.0336)	(0.00619)	(0.0356)	(0.00989)	(0.0684)
Size (lag)	0.0303***	0.0736*	0.0346***	0.0994**	0.0331***	0.117*	0.0255***	0.0421***
	(0.00658)	(0.0290)	(0.00655)	(0.0314)	(0.00565)	(0.0543)	(0.00345)	(0.0111)
Productivity (lag)	-0.0339***	-0.0503*	-0.0376***	-0.0665**	-0.0378***	-0.0744*	-0.0440***	-0.0774*
	(0.00845)	(0.0222)	(0.00847)	(0.0234)	(0.00877)	(0.0348)	(0.00853)	(0.0314)
R&D intensity (lag)	1.201***	0.969*	1.163***	1.041**	1.102***	1.023*	1.166***	0.639
	(0.227)	(0.478)	(0.204)	(0.398)	(0.234)	(0.520)	(0.220)	(0.351)
P-score	-0.0715	-0.311	-0.205*	-0.744*	-0.284	-1.053	-0.561***	-1.769
	(0.0618)	(0.163)	(0.0940)	(0.308)	(0.145)	(0.612)	(0.145)	(0.948)
Constant	0.133	0.0907	0.156*	0.109	0.168*	0.0802	0.187*	0.306
	(0.0801)	(0.146)	(0.0768)	(0.124)	(0.0799)	(0.145)	(0.0817)	(0.172)
Observations	8724	2969	8724	2969	8724	2969	8724	2969

Notes: Split-sample OLS estimates of Equation (3) by small-medium enterprises (SMES, employees ≤ 250) and large firms (Large, employees > 250). Bootstrap standard errors in parenthesis (100 replications). Asterisks denote significance levels: * $p<0.05$, ** $p<0.01$, *** $p<0.001$.

Table 12: Innovation persistence and persistence of firm growth - SMES vs. Large firms

	R&D		PROCESS		PRODUCT		PATENT	
	SMEs	Large	SMEs	Large	SMEs	Large	SMEs	Large
PERS dummy	-0.0114	-0.00000728	0.00444	-0.0132	0.0302*	0.000103	0.00864	0.0362
	(0.0132)	(0.0136)	(0.00969)	(0.0106)	(0.0140)	(0.0160)	(0.0334)	(0.0227)
Sales Growth (lag)	-0.0223	-0.0272	-0.0197	-0.0335	-0.0393	-0.0134	-0.0362	0.0103
	(0.0199)	(0.0671)	(0.0228)	(0.0404)	(0.0245)	(0.0394)	(0.0234)	(0.0360)
Interaction	-0.152	0.0507	-0.0925	0.0934	-0.0593	0.115	-0.297	0.157
	(0.120)	(0.0747)	(0.0804)	(0.0609)	(0.0789)	(0.118)	(0.264)	(0.114)
Age	0.00148	0.0339	0.00763	0.0698	0.00112	0.0557	0.0302*	0.129
	(0.00624)	(0.0251)	(0.00828)	(0.0464)	(0.00662)	(0.0344)	(0.0122)	(0.0753)
Size (lag)	0.0355***	0.0854**	0.0401***	0.113*	0.0381***	0.134**	0.0272***	0.0454***
	(0.00649)	(0.0272)	(0.00671)	(0.0463)	(0.00700)	(0.0492)	(0.00408)	(0.0123)
Productivity (lag)	-0.0318***	-0.0535*	-0.0367***	-0.0716*	-0.0366***	-0.0806**	-0.0412***	-0.0838*
	(0.00824)	(0.0241)	(0.00801)	(0.0339)	(0.00946)	(0.0307)	(0.00892)	(0.0348)
R&D intensity (lag)	1.227***	1.144*	1.165***	1.203*	1.096***	1.197*	1.141***	0.694*
	(0.229)	(0.488)	(0.241)	(0.536)	(0.220)	(0.494)	(0.206)	(0.315)
P-score	-0.115	-0.390*	-0.268**	-0.887	-0.377*	-1.257*	-0.551***	-1.992
	(0.0647)	(0.168)	(0.103)	(0.465)	(0.147)	(0.559)	(0.159)	(1.021)
Constant	0.0942	0.0847	0.128	0.104	0.142	0.0716	0.151*	0.340
	(0.0785)	(0.158)	(0.0763)	(0.154)	(0.0855)	(0.153)	(0.0735)	(0.191)
Observations	7646	2600	7646	2600	7646	2600	7646	2600

Notes: Split-sample OLS estimates of Equation (4) by small-medium enterprises (SMES, employees $\leq$ 250) and large firms (Large, employees $>$ 250). Bootstrap standard errors in parenthesis (100 replications). Asterisks denote significance levels: * p<0.05, ** p<0.01, *** p<0.001.

In other words, although all groups of persistent innovators that we identify surely encompass small and large firms, we may have found that persistent innovators do not grow more and do not show more growth persistence just because they are larger than the other firms. The descriptive analysis in Section 5 gives some support that this might indeed be the case in our data: persistent innovators are much larger and display less dispersed growth rates than other firms.

Just controlling for size,as we do in the main analysis, does not allow to explore the interaction between size and innovation persistence.[12] To shed further light on the role of firm size, we provide a split sample analysis. We first divide the sample between small-medium enterprises (SMEs, with employees $\leq$250) and large firms (Large, employees >250) according to the number of employees reported in 2000, i.e. the initial year of the regression time period 2000-2012. Next, we re-estimate our baseline regression models in Equation (3) and Equation (4) separately on the two groups of SMEs and Large firms. The research questions, thus, change sensibly. We now ask whether small-medium persistent innovators differ from other small-medium firms, and whether large persistent innovators differ from other large firms.

The results of this additional analysis are reported in Table 11 and Table 12. They support that the findings from the main analysis do not completely stem from a sheer size effect. No matter the proxy of innovation persistence considered, the coefficients on the $PERS$ dummy are insignificant in the specification modeling the relation between persistent innovation and average growth (in Table 11). Similarly, we do not find variation across size categories in the estimated interaction coefficients in the specification modeling the relation between persistent innovation and persistence in growth patterns (in Table 12): they are all statistically zero, across all the dimensions of innovation persistence.

7.2 Asymmetries along firm growth quantiles

We conclude our empirical analysis with a quantile regression exercise, allowing to explore the variation of coefficient estimates along the entire distribution of sales growth rates. Recent findings in the micro-empirics of the innovation-growth nexus suggest that innovation may be specifically beneficial for high-growth firms in the top quantiles of the growth rates distribution. There are no studies to our knowledge asking whether innovation persistence is similarly related to extraordinary growth performance in the top quantiles. Perhaps, it could be that exactly in the top quantiles we will be able to verify our hypotheses that persistent innovators outperform other firms.

We re-estimate our baseline models in Equation (3) and Equation (4) via standard conditional quantile regressions (Koenker and Bassett, 1978), including all the firm-level controls, but without p-scores.[13] The estimates obtained on the coefficients of primer interest in the two

[12] The comments of an anonymous referee were crucial to recognize this point.

[13] In fact, including p-scores would assume that innovation persistence propensity is constant across quantiles, which is at odds with a genuine interest in quantile effects. We thank a referee for pointing this out. Also note that we do not include sector fixed-effects in the quantile estimates: given the relatively small number of persistent innovators, we cannot identify sector-specific intercepts in the growth quantiles.

models are reported, respectively, in Table 13 and Table 14.[14]

Regarding the first research question (in Table 13), we find some heterogeneity across persistence innovation indicators. Persistent R&D innovators, indeed, display lower growth rates (conditional on other factors) than other firms along most of the quantiles. This replicate the average effects already observed in the main estimates (simple OLS without p-scores). Conversely, firms persistently innovating in products or processes, as well as persistently patenting firms all show negative growth premia only for high-growth firms in the top quantiles. Note also that the average growth of persistent innovators (constant plus coefficient β_1) also turns from negative among low-growth or shrinking firms, to positive among firms around the top quantiles, conditional on other factors. Size effects can play some role in this, due to lower growth dispersion among large firms, but we cannot provide a split-sample analysis by firm size here, due to the already low number of data points for persistent innovators presumably featuring some of the quantiles.

The findings about growth persistence premia (in Table 14), are quite consistent across different innovation variables. The coefficients on the interaction terms between the $PERS$ dummies and lagged growth are never statistically significant. This provides another bit of evidence that persistent innovators do not show significantly different autocorrelation structures compared to other firms.

8 Conclusion

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 of growth and success in the market, as compared to the other firms populating the economy. This paper contributes to fill this empirical gap. We ask whether persistent innovators grow more and if they display more persistent growth paths

To address these questions, 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. Yearly data offer the opportunity to overcome 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 between innovation persistence and firm growth trajectories. Further, we account for the heterogeneity characterizing four different types of innovation activity (R&D expenditure, product and process innovation, patenting) in terms of (i) their theoretically heterogeneous relations with sales growth, and (ii) their characterization as delivering weak vs. strong measures of innovation persistence.

Our analyses convey a clear finding: persistent innovators do not grow more, on average, and they do not display higher persistence in their growth dynamics. These results are robust across the different dimensions of innovation activity considered, although we found some signal that

[14]For completeness, tables reporting the full set of coefficients are presented in Appendix B.

Table 13: Innovation persistence and firm growth - Quantile regressions

		q10	q20	q30	q40	q50	q60	q70	q80	q90
R&D	PERS dummy	-0.00244	-0.0149*	-0.0150**	-0.0174***	-0.0118**	-0.0114**	-0.0137*	-0.0144*	-0.0202
		(0.0124)	(0.00698)	(0.00459)	(0.00422)	(0.00406)	(0.00435)	(0.00553)	(0.00666)	(0.0110)
	Constant	-0.558***	-0.437***	-0.301***	-0.208***	-0.112***	-0.00840	0.0855*	0.270***	0.521***
		(0.0847)	(0.0490)	(0.0380)	(0.0285)	(0.0301)	(0.0284)	(0.0375)	(0.0471)	(0.0612)
PROCESS	PERS dummy	0.0160	0.000891	0.00196	-0.00150	-0.00137	-0.00292	-0.00514	-0.00944*	-0.0207**
		(0.00895)	(0.00485)	(0.00385)	(0.00344)	(0.00289)	(0.00318)	(0.00395)	(0.00396)	(0.00747)
	Constant	-0.566***	-0.423***	-0.305***	-0.194***	-0.102***	0.0000205	0.0850*	0.282***	0.527***
		(0.0674)	(0.0395)	(0.0346)	(0.0276)	(0.0308)	(0.0272)	(0.0365)	(0.0422)	(0.0594)
PRODUCT	PERS dummy	0.0256	0.00590	0.00473	0.00168	-0.000713	-0.00100	-0.00800	-0.0213**	-0.0223
		(0.0166)	(0.00793)	(0.00656)	(0.00576)	(0.00616)	(0.00533)	(0.00686)	(0.00746)	(0.0166)
	Constant	-0.557***	-0.420***	-0.302***	-0.191***	-0.0958**	0.000560	0.0933*	0.293***	0.540***
		(0.0789)	(0.0443)	(0.0378)	(0.0301)	(0.0320)	(0.0297)	(0.0384)	(0.0424)	(0.0570)
PATENTS	PERS dummy	0.0203	0.00636	0.00982	0.00859	0.00203	-0.00150	-0.000349	-0.0272**	-0.0465
		(0.0217)	(0.0156)	(0.00997)	(0.0122)	(0.00854)	(0.0107)	(0.00967)	(0.00925)	(0.0282)
	Constant	-0.559***	-0.419***	-0.304***	-0.193***	-0.100**	0.000126	0.0888*	0.298***	0.531***
		(0.0684)	(0.0450)	(0.0343)	(0.0295)	(0.0309)	(0.0286)	(0.0365)	(0.0425)	(0.0611)
Observations		11937	11937	11937	11937	11937	11937	11937	11937	11937

Notes: Simultaneous quantile regression estimates of Equation (3). Bootstrap standard errors in parenthesis (100 replications). Asterisks denote significance levels: *p<0.05, ** p<0.01, *** p<0.001.

Table 14: Innovation persistence and persistence of firm growth - Quantile regressions

		q10	q20	q30	q40	q50	q60	q70	q80	q90
R&D	PERS dummy	-0.00501	-0.0122	-0.0151**	-0.0170***	-0.0130**	-0.0116*	-0.0142**	-0.0137*	-0.0205
		(0.0129)	(0.00763)	(0.00461)	(0.00415)	(0.00442)	(0.00451)	(0.00521)	(0.00644)	(0.0121)
	Sales Growth (lag)	0.0192	0.0393*	0.0458***	0.0378**	0.0293*	0.0359**	0.0295	0.00447	-0.0310
		(0.0223)	(0.0177)	(0.0133)	(0.0133)	(0.0147)	(0.0125)	(0.0179)	(0.0162)	(0.0197)
	Interaction	-0.0315	-0.0118	-0.0166	-0.0127	-0.0166	-0.0358	-0.0317	-0.0186	-0.0152
		(0.0436)	(0.0277)	(0.0177)	(0.0167)	(0.0204)	(0.0229)	(0.0221)	(0.0223)	(0.0324)
	Constant	-0.641***	-0.456***	-0.306***	-0.216***	-0.106**	-0.0128	0.0874*	0.257***	0.436***
		(0.0895)	(0.0561)	(0.0428)	(0.0339)	(0.0349)	(0.0346)	(0.0384)	(0.0501)	(0.0666)
PROCESS	PERS dummy	0.0148	-0.000702	0.00275	0.000265	-0.000808	-0.00494	-0.00623	-0.00933	-0.0215*
		(0.00976)	(0.00599)	(0.00435)	(0.00422)	(0.00360)	(0.00424)	(0.00471)	(0.00620)	(0.00996)
	Sales Growth (lag)	0.0149	0.0384*	0.0476***	0.0377***	0.0283*	0.0281*	0.0185	0.00329	-0.0374
		(0.0276)	(0.0165)	(0.0107)	(0.0109)	(0.0135)	(0.0126)	(0.0161)	(0.0146)	(0.0193)
	Interaction	0.00162	-0.00695	-0.0235	-0.00783	0.000412	-0.00238	-0.00447	-0.0136	0.0314
		(0.0362)	(0.0246)	(0.0181)	(0.0151)	(0.0214)	(0.0200)	(0.0300)	(0.0316)	(0.0450)
	Constant	-0.655***	-0.447***	-0.298***	-0.191***	-0.0911**	-0.00190	0.0805*	0.271***	0.467***
		(0.0844)	(0.0553)	(0.0410)	(0.0312)	(0.0306)	(0.0307)	(0.0359)	(0.0482)	(0.0637)
PRODUCT	PERS dummy	0.0229	0.00586	0.00871	0.00394	0.00469	-0.00239	-0.00949	-0.0192*	-0.0259
		(0.0158)	(0.0112)	(0.00672)	(0.00516)	(0.00593)	(0.00480)	(0.00717)	(0.00811)	(0.0150)
	Sales Growth (lag)	0.0183	0.0367**	0.0436***	0.0358***	0.0284*	0.0302*	0.0203	-0.00250	-0.0367*
		(0.0207)	(0.0133)	(0.00978)	(0.00967)	(0.0127)	(0.0123)	(0.0163)	(0.0140)	(0.0167)
	Interaction	-0.0912	-0.0457	-0.0303	-0.0188	-0.0112	0.00745	0.00705	0.0291	0.110*
		(0.0796)	(0.0736)	(0.0477)	(0.0356)	(0.0347)	(0.0389)	(0.0445)	(0.0451)	(0.0524)
	Constant	-0.629***	-0.449***	-0.290***	-0.188***	-0.0879**	-0.000730	0.0926*	0.280***	0.473***
		(0.0812)	(0.0617)	(0.0420)	(0.0303)	(0.0311)	(0.0327)	(0.0409)	(0.0426)	(0.0598)
PATENTS	PERS dummy	0.0157	0.0204	0.00663	0.00567	0.00109	-0.00450	-0.00253	-0.0306**	-0.0699
		(0.0223)	(0.0175)	(0.0111)	(0.0140)	(0.0105)	(0.0140)	(0.0134)	(0.0106)	(0.0432)
	Sales Growth (lag)	0.0164	0.0343**	0.0387***	0.0355***	0.0284**	0.0292**	0.0203	0.00125	-0.0314
		(0.0194)	(0.0130)	(0.0105)	(0.00880)	(0.0107)	(0.0112)	(0.0142)	(0.0125)	(0.0173)
	Interaction	0.140	0.0465	0.0248	-0.0197	-0.0231	-0.0324	-0.0758	-0.00654	-0.0589
		(0.124)	(0.100)	(0.0674)	(0.0793)	(0.0766)	(0.108)	(0.113)	(0.112)	(0.274)
	Constant	-0.639***	-0.448***	-0.299***	-0.189***	-0.0881**	-0.00489	0.0875*	0.285***	0.459***
		(0.0804)	(0.0484)	(0.0350)	(0.0298)	(0.0297)	(0.0308)	(0.0349)	(0.0424)	(0.0597)
Observations		10447	10447	10447	10447	10447	10447	10447	10447	10447

Notes: Simultaneous quantile regression estimates of Equation (4). Bootstrap standard errors in parenthesis (100 replications). Asterisks denote significance levels: *p<0.05, ** p<0.01, *** p<0.001.

persistent R&D innovators may even grow less than other firms. Moreover, the main results are invariant to different estimation methods, to an alternative notion of growth persistence in terms of transition matrices, and across small-medium vs. larger firms. Lastly, results essentially survive along the quantiles of the growth rates distribution, although we find that persistent innovators may even grow less than other firms in some quantiles, mostly in the top ones.

As they stand out, our findings are at odds with our working hypotheses and contrast with most existing theories of innovation persistence, that share the view that persistent innovators represent an elite of “champion firms”, able to constantly out-compete other firms, both on average and over time.

At least part of the explanation for our negative result can be related to the nature of the different innovation dimensions that we consider. Uncertainty of various kind are known to potentially cloud the relation between persistence in R&D and success on the market. Persistent process innovations often involve restructuring that display more direct effects on cost efficiency, only indirectly passing through growth in the market. More puzzling is that we do not find any significant result for firms that persistently engage in innovation activities more closely related to market performance, such as product innovation and patenting. A speculative interpretation could be that most of the new products and patents introduced concern non-radical, relatively marginal innovations that do not support an extraordinary growth performance in the following years. Unfortunately, we do not have information about patents and products characteristics to further validate this interpretation.

An alternative explanatory framework is surely offered by theories conceptualizing firm growth as well approximated by a random process, or essentially stemming from chance. This view is supported by previous empirical studies that it found it difficult to identify strong predictors of firm growth and firm growth persistence. Our findings add that growth patterns may be highly unstable and difficult to predict also for persistent innovators.

We can foresee a number of extensions to further corroborate our analysis in future work, in turn posing interesting questions not yet tested in our study. The perhaps more urgent open question to address is about the factors impeding innovation persistence to pay-off in terms of sales growth dynamics. Is it just that growth in the market, in the end, stems from idiosyncratic features and perhaps luck, or are there firm-specific capabilities and resources at a finer level, within the firms, that we cannot measure here? Or, alternatively, are there external factors, like barriers to innovation and barriers to growth, that eventually play behind our findings? Our framework is surely suited to analyse these issues, but more data would be needed.

Another question, that we cannot address at this stage with our data, concerns whether it is the “intensity of innovation persistence” that may eventually deliver growth premia to persistent innovators. That is, we here measure innovation persistence in terms of frequency of innovation efforts, by counting if firms repeat a given innovation activity consecutively over time. It would be interesting to also characterize persistent innovators by the magnitude of their consecutive innovative efforts, e.g. by the size of their R&D investment, the number and type of product and process innovations, or the quality and value of patents. This kind of analysis would make an interesting connection to the literature on sources and persistence of technological leadership and their relations to industrial dynamics.

These open questions yet to be explored, as well as the need to further test our conclusions on data on different countries, suggest that it could be too early to derive sharp policy implications. Nonetheless, with all their limitations, our results so far cast doubts that policy makers could rely upon nurturing persistent innovators to promote growth of sectors and countries. Persistent innovators do exist and may even exhibit particularly outstanding performance in some specific circumstances. Yet, they are not generally able to grow more and more persistently than other firms.

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Appendix A: Control variables

We here present standard preliminary analysis of the correlations among control variables, and among controls and the dependent variable, providing background evidence in interpreting our main regression analysis. First, in Table 15, we show the pairwise correlations. Notice that those between controls are all relatively low, reassuring that the main estimates do not suffer from significant collinearity. Second, in Table 9 we explore the relation between the dependent variable and the controls (one by one and all together), in models excluding the main regressor $PERS$. Results replicate the patterns observed in the main analysis, reassuring that the controls are indeed good controls.

Table 15: Pairwise correlations

	G_t	G_{t-1}	Age	Size (lag)	Productivity (lag)	R&D intensity (lag)
G_t	1.0000					
G_{t-1}	-0.0052	1.0000				
Age	-0.0185	-0.0137	1.0000			
Size (lag)	0.0558*	0.1048*	0.3541*	1.0000		
Productivity (lag)	-0.0147	0.1712*	0.3236*	0.5058*	1.0000	
R&D intensity (lag)	0.1800*	-0.0535*	0.0187	0.0456*	0.1010*	1.0000

Notes: Asterisks denote significance at 1% confidence level (Bonferroni adjusted).

Table 16: Controls and firm growth, excluding $PERS$

Dep. Variable is G_{t-1}	(1)	(2)	(3)	(4)	(5)	(6)	(7)
G_{t-1}	-0.00551						0.00905
	(0.0182)						(0.0157)
Age		-0.00871**				-0.0144***	-0.0124**
		(0.00331)				(0.00406)	(0.00434)
Size (lag)			0.0123***			0.0193***	0.0185***
			(0.00139)			(0.00201)	(0.00214)
Productivity (lag)				-0.00658		-0.0251***	-0.0227***
				(0.00418)		(0.00543)	(0.00542)
R&D intensity (lag)					0.631***	0.640***	0.718***
					(0.0251)	(0.142)	(0.143)
Constant	-0.0281***	0.0107	-0.0691***	0.0456	-0.0223***	0.198***	0.162**
	(0.00240)	(0.0111)	(0.00647)	(0.0434)	(0.00214)	(0.0501)	(0.0503)
Observations	16530	18849	19815	17931	19745	17304	15810

Notes: OLS regressions. Robust standard errors in parenthesis. Asterisks denote significance levels: * $p<0.05$, ** $p<0.01$, *** $p<0.001$.

Appendix B: Quantile regressions, full results

Table 17: R&D persistence and firm growth - Quantile regressions

	q10	q20	q30	q40	q50	q60	q70	q80	q90
PERS dummy	-0.00244	-0.0149*	-0.0150**	-0.0174***	-0.0118**	-0.0114**	-0.0137*	-0.0144*	-0.0202
	(0.0124)	(0.00698)	(0.00459)	(0.00422)	(0.00406)	(0.00435)	(0.00553)	(0.00666)	(0.0110)
Age	0.0174	0.00572	0.00256	-0.000970	-0.00554*	-0.00790**	-0.0127***	-0.0195***	-0.0213**
	(0.0101)	(0.00451)	(0.00305)	(0.00293)	(0.00238)	(0.00260)	(0.00314)	(0.00366)	(0.00713)
Size (lag)	0.0243***	0.0177***	0.0128***	0.00845***	0.00649***	0.00488***	0.00407*	0.00497*	0.00514
	(0.00318)	(0.00189)	(0.00121)	(0.00115)	(0.00127)	(0.00122)	(0.00172)	(0.00203)	(0.00344)
Productivity (lag)	0.00722	0.0127**	0.00859*	0.00694*	0.00304	-0.00199	-0.00512	-0.0156***	-0.0323***
	(0.00833)	(0.00473)	(0.00348)	(0.00275)	(0.00309)	(0.00275)	(0.00392)	(0.00442)	(0.00613)
R&D intensity (lag)	0.187	0.268	0.326**	0.339***	0.401***	0.449***	0.602***	0.769***	0.832**
	(0.194)	(0.156)	(0.105)	(0.0946)	(0.0979)	(0.109)	(0.123)	(0.144)	(0.315)
Constant	-0.558***	-0.437***	-0.301***	-0.208***	-0.112***	-0.00840	0.0855*	0.270***	0.521***
	(0.0847)	(0.0490)	(0.0380)	(0.0285)	(0.0301)	(0.0284)	(0.0375)	(0.0471)	(0.0612)
Observations	11937	11937	11937	11937	11937	11937	11937	11937	11937

Notes: Simultaneous quantile regression estimates of Equation (3). Bootstrap standard errors in parenthesis (100 replications). Asterisks denote significance levels: *p<0.05, ** p<0.01, *** p<0.001.

Table 18: Process Innovation persistence and firm growth - Quantile regressions

	q10	q20	q30	q40	q50	q60	q70	q80	q90
PERS dummy	0.0160	0.000891	0.00196	-0.00150	-0.00137	-0.00292	-0.00514	-0.00944*	-0.0207**
	(0.00895)	(0.00485)	(0.00385)	(0.00344)	(0.00289)	(0.00318)	(0.00395)	(0.00396)	(0.00747)
Age	0.0174*	0.00306	0.00169	-0.00220	-0.00625*	-0.00957***	-0.0131***	-0.0198***	-0.0210**
	(0.00836)	(0.00461)	(0.00350)	(0.00270)	(0.00246)	(0.00266)	(0.00289)	(0.00385)	(0.00685)
Size (lag)	0.0232***	0.0153***	0.0101***	0.00670***	0.00480***	0.00402**	0.00225	0.00395*	0.00559
	(0.00282)	(0.00191)	(0.00166)	(0.00147)	(0.00132)	(0.00140)	(0.00178)	(0.00189)	(0.00331)
Productivity (lag)	0.00828	0.0122**	0.00967**	0.00667*	0.00284	-0.00193	-0.00453	-0.0164***	-0.0334***
	(0.00670)	(0.00398)	(0.00326)	(0.00278)	(0.00314)	(0.00271)	(0.00388)	(0.00418)	(0.00640)
R&D intensity (lag)	0.123	0.178	0.255**	0.252**	0.364***	0.404***	0.563***	0.695***	0.701**
	(0.171)	(0.145)	(0.0967)	(0.0771)	(0.0930)	(0.0937)	(0.120)	(0.128)	(0.255)
Constant	-0.566***	-0.423***	-0.305***	-0.194***	-0.102***	0.0000205	0.0850*	0.282***	0.527***
	(0.0674)	(0.0395)	(0.0346)	(0.0276)	(0.0308)	(0.0272)	(0.0365)	(0.0422)	(0.0594)
Observations	11937	11937	11937	11937	11937	11937	11937	11937	11937

Notes: Simultaneous quantile regression estimates of Equation (3). Bootstrap standard errors in parenthesis (100 replications). Asterisks denote significance levels: *p<0.05, ** p<0.01, *** p<0.001.

Table 19: Product Innovation persistence and firm growth - Quantile regressions

	q10	q20	q30	q40	q50	q60	q70	q80	q90
PERS dummy	0.0256	0.00590	0.00473	0.00168	-0.000713	-0.00100	-0.00800	-0.0213**	-0.0223
	(0.0166)	(0.00793)	(0.00656)	(0.00576)	(0.00616)	(0.00533)	(0.00686)	(0.00746)	(0.0166)
Age	0.0187*	0.00344	0.00174	-0.00246	-0.00646*	-0.0102***	-0.0141***	-0.0209***	-0.0241***
	(0.00786)	(0.00470)	(0.00320)	(0.00312)	(0.00272)	(0.00279)	(0.00319)	(0.00344)	(0.00686)
Size (lag)	0.0232***	0.0153***	0.0102***	0.00664***	0.00489***	0.00370**	0.00257	0.00474*	0.00354
	(0.00303)	(0.00189)	(0.00141)	(0.00150)	(0.00128)	(0.00139)	(0.00171)	(0.00197)	(0.00309)
Productivity (lag)	0.00711	0.0118**	0.00958**	0.00656*	0.00233	-0.00155	-0.00501	-0.0174***	-0.0330***
	(0.00813)	(0.00450)	(0.00360)	(0.00313)	(0.00339)	(0.00311)	(0.00408)	(0.00421)	(0.00631)
R&D intensity (lag)	0.121	0.173	0.230*	0.253**	0.364***	0.398***	0.547***	0.738***	0.734**
	(0.152)	(0.147)	(0.113)	(0.0825)	(0.0873)	(0.0977)	(0.111)	(0.120)	(0.271)
Constant	-0.557***	-0.420***	-0.302***	-0.191***	-0.0958**	0.000560	0.0933*	0.293***	0.540***
	(0.0789)	(0.0443)	(0.0378)	(0.0301)	(0.0320)	(0.0297)	(0.0384)	(0.0424)	(0.0570)
Observations	11937	11937	11937	11937	11937	11937	11937	11937	11937

Notes: Simultaneous quantile regression estimates of Equation (3). Bootstrap standard errors in parenthesis (100 replications). Asterisks denote significance levels: *p<0.05, ** p<0.01, *** p<0.001.

Table 20: Patenting persistence and firm growth - Quantile regressions

	q10	q20	q30	q40	q50	q60	q70	q80	q90
PERS dummy	0.0203	0.00636	0.00982	0.00859	0.00203	-0.00150	-0.000349	-0.0272**	-0.0465
	(0.0217)	(0.0156)	(0.00997)	(0.0122)	(0.00854)	(0.0107)	(0.00967)	(0.00925)	(0.0282)
Age	0.0166	0.00330	0.00208	-0.00231	-0.00626*	-0.0101***	-0.0141***	-0.0208***	-0.0228**
	(0.00912)	(0.00433)	(0.00308)	(0.00329)	(0.00297)	(0.00271)	(0.00356)	(0.00416)	(0.00752)
Size (lag)	0.0239***	0.0153***	0.0101***	0.00661***	0.00482***	0.00365**	0.00212	0.00514**	0.00494
	(0.00293)	(0.00169)	(0.00139)	(0.00127)	(0.00126)	(0.00115)	(0.00157)	(0.00176)	(0.00285)
Productivity (lag)	0.00783	0.0117*	0.00959**	0.00672*	0.00269	-0.00158	-0.00470	-0.0181***	-0.0335***
	(0.00731)	(0.00460)	(0.00331)	(0.00295)	(0.00323)	(0.00311)	(0.00412)	(0.00464)	(0.00667)
R&D intensity (lag)	0.157	0.172	0.250*	0.239*	0.359***	0.397***	0.559***	0.749***	0.735**
	(0.169)	(0.134)	(0.107)	(0.0978)	(0.0990)	(0.0925)	(0.112)	(0.122)	(0.265)
Constant	-0.559***	-0.419***	-0.304***	-0.193***	-0.100**	0.000126	0.0888*	0.298***	0.531***
	(0.0684)	(0.0450)	(0.0343)	(0.0295)	(0.0309)	(0.0286)	(0.0365)	(0.0425)	(0.0611)
Observations	11937	11937	11937	11937	11937	11937	11937	11937	11937

Notes: Simultaneous quantile regression estimates of Equation (3). Bootstrap standard errors in parenthesis (100 replications). Asterisks denote significance levels: *p<0.05, ** p<0.01, *** p<0.001.

Table 21: R&D persistence and persistence of firm growth - Quantile regressions

	q10	q20	q30	q40	q50	q60	q70	q80	q90
PERS dummy	-0.00501	-0.0122	-0.0151**	-0.0170***	-0.0130**	-0.0116*	-0.0142**	-0.0137*	-0.0205
	(0.0129)	(0.00763)	(0.00461)	(0.00415)	(0.00442)	(0.00451)	(0.00521)	(0.00644)	(0.0121)
Sales Growth (lag)	0.0192	0.0393*	0.0458***	0.0378**	0.0293*	0.0359**	0.0295	0.00447	-0.0310
	(0.0223)	(0.0177)	(0.0133)	(0.0133)	(0.0147)	(0.0125)	(0.0179)	(0.0162)	(0.0197)
Interaction	-0.0315	-0.0118	-0.0166	-0.0127	-0.0166	-0.0358	-0.0317	-0.0186	-0.0152
	(0.0436)	(0.0277)	(0.0177)	(0.0167)	(0.0204)	(0.0229)	(0.0221)	(0.0223)	(0.0324)
Age	0.0154	0.00753	0.00532	0.000344	-0.00423	-0.00716*	-0.0145***	-0.0216***	-0.0220**
	(0.0101)	(0.00518)	(0.00358)	(0.00295)	(0.00302)	(0.00318)	(0.00317)	(0.00379)	(0.00811)
Size (lag)	0.0264***	0.0180***	0.0140***	0.00961***	0.00785***	0.00583***	0.00523**	0.00572**	0.00534
	(0.00297)	(0.00213)	(0.00182)	(0.00141)	(0.00133)	(0.00133)	(0.00178)	(0.00219)	(0.00307)
Productivity (lag)	0.0144	0.0135*	0.00772	0.00649	0.00159	-0.00214	-0.00525	-0.0139**	-0.0241***
	(0.00865)	(0.00545)	(0.00425)	(0.00338)	(0.00363)	(0.00376)	(0.00433)	(0.00490)	(0.00674)
R&D intensity (lag)	0.130	0.182	0.285**	0.317***	0.398***	0.472***	0.584***	0.740***	0.812**
	(0.193)	(0.150)	(0.104)	(0.0883)	(0.0936)	(0.0988)	(0.112)	(0.125)	(0.254)
Constant	-0.641***	-0.456***	-0.306***	-0.216***	-0.106**	-0.0128	0.0874*	0.257***	0.436***
	(0.0895)	(0.0561)	(0.0428)	(0.0339)	(0.0349)	(0.0346)	(0.0384)	(0.0501)	(0.0666)
Observations	10447	10447	10447	10447	10447	10447	10447	10447	10447

Notes: Simultaneous quantile regression estimates of Equation (4). Bootstrap standard errors in parenthesis (100 replications). Asterisks denote significance levels: *p<0.05, ** p<0.01, *** p<0.001.

Table 22: Process Innovation persistence and persistence of firm growth - Quantile regressions

	q10	q20	q30	q40	q50	q60	q70	q80	q90
PERS dummy	0.0148	-0.000702	0.00275	0.000265	-0.000808	-0.00494	-0.00623	-0.00933	-0.0215*
	(0.00976)	(0.00599)	(0.00435)	(0.00422)	(0.00360)	(0.00424)	(0.00471)	(0.00620)	(0.00996)
Sales Growth (lag)	0.0149	0.0384*	0.0476***	0.0377***	0.0283*	0.0281*	0.0185	0.00329	-0.0374
	(0.0276)	(0.0165)	(0.0107)	(0.0109)	(0.0135)	(0.0126)	(0.0161)	(0.0146)	(0.0193)
Interaction	0.00162	-0.00695	-0.0235	-0.00783	0.000412	-0.00238	-0.00447	-0.0136	0.0314
	(0.0362)	(0.0246)	(0.0181)	(0.0151)	(0.0214)	(0.0200)	(0.0300)	(0.0316)	(0.0450)
Age	0.0134	0.00524	0.00458	-0.000883	-0.00531	-0.00794**	-0.0146***	-0.0217***	-0.0235**
	(0.00933)	(0.00519)	(0.00377)	(0.00314)	(0.00291)	(0.00272)	(0.00290)	(0.00383)	(0.00735)
Size (lag)	0.0239***	0.0161***	0.0116***	0.00813***	0.00603***	0.00476***	0.00294	0.00462*	0.00504
	(0.00309)	(0.00211)	(0.00185)	(0.00152)	(0.00141)	(0.00139)	(0.00197)	(0.00231)	(0.00320)
Productivity (lag)	0.0177*	0.0139**	0.00699	0.00488	0.00104	-0.00261	-0.00372	-0.0149**	-0.0264***
	(0.00849)	(0.00533)	(0.00375)	(0.00336)	(0.00321)	(0.00325)	(0.00403)	(0.00466)	(0.00687)
R&D intensity (lag)	0.0644	0.124	0.244**	0.241**	0.346***	0.392***	0.532***	0.678***	0.760**
	(0.169)	(0.127)	(0.0937)	(0.0828)	(0.101)	(0.0968)	(0.128)	(0.122)	(0.261)
Constant	-0.655***	-0.447***	-0.298***	-0.191***	-0.0911**	-0.00190	0.0805*	0.271***	0.467***
	(0.0844)	(0.0553)	(0.0410)	(0.0312)	(0.0306)	(0.0307)	(0.0359)	(0.0482)	(0.0637)
Observations	10447	10447	10447	10447	10447	10447	10447	10447	10447

Notes: Simultaneous quantile regression estimates of Equation (4). Bootstrap standard errors in parenthesis (100 replications). Asterisks denote significance levels: *p<0.05, ** p<0.01, *** p<0.001.

Table 23: Product Innovation persistence and persistence of firm growth - Quantile regressions

	q10	q20	q30	q40	q50	q60	q70	q80	q90
PERS dummy	0.0229	0.00586	0.00871	0.00394	0.00469	-0.00239	-0.00949	-0.0192*	-0.0259
	(0.0158)	(0.0112)	(0.00672)	(0.00516)	(0.00593)	(0.00480)	(0.00717)	(0.00811)	(0.0150)
Sales Growth (lag)	0.0183	0.0367**	0.0436***	0.0358***	0.0284*	0.0302*	0.0203	-0.00250	-0.0367*
	(0.0207)	(0.0133)	(0.00978)	(0.00967)	(0.0127)	(0.0123)	(0.0163)	(0.0140)	(0.0167)
Interaction	-0.0912	-0.0457	-0.0303	-0.0188	-0.0112	0.00745	0.00705	0.0291	0.110*
	(0.0796)	(0.0736)	(0.0477)	(0.0356)	(0.0347)	(0.0389)	(0.0445)	(0.0451)	(0.0524)
Age	0.0146	0.00527	0.00467	-0.00106	-0.00565*	-0.00946**	-0.0149***	-0.0220***	-0.0242**
	(0.00918)	(0.00498)	(0.00292)	(0.00308)	(0.00281)	(0.00299)	(0.00356)	(0.00419)	(0.00767)
Size (lag)	0.0254***	0.0158***	0.0115***	0.00816***	0.00620***	0.00477***	0.00299	0.00496*	0.00453
	(0.00367)	(0.00227)	(0.00178)	(0.00159)	(0.00138)	(0.00129)	(0.00177)	(0.00198)	(0.00298)
Productivity (lag)	0.0141	0.0139*	0.00674	0.00474	0.000823	-0.00214	-0.00490	-0.0160***	-0.0267***
	(0.00842)	(0.00642)	(0.00424)	(0.00336)	(0.00345)	(0.00338)	(0.00432)	(0.00446)	(0.00616)
R&D intensity (lag)	0.115	0.133	0.182	0.240**	0.346***	0.395***	0.524***	0.739***	0.675**
	(0.159)	(0.139)	(0.116)	(0.0908)	(0.0923)	(0.0851)	(0.111)	(0.121)	(0.242)
Constant	-0.629***	-0.449***	-0.290***	-0.188***	-0.0879**	-0.000730	0.0926*	0.280***	0.473***
	(0.0812)	(0.0617)	(0.0420)	(0.0303)	(0.0311)	(0.0327)	(0.0409)	(0.0426)	(0.0598)
Observations	10447	10447	10447	10447	10447	10447	10447	10447	10447

Notes: Simultaneous quantile regression estimates of Equation (4). Bootstrap standard errors in parenthesis (100 replications). Asterisks denote significance levels: *p<0.05, ** p<0.01, *** p<0.001.

Table 24: Patenting persistence and persistence of firm growth - Quantile regressions

	q10	q20	q30	q40	q50	q60	q70	q80	q90
PERS dummy	0.0157	0.0204	0.00663	0.00567	0.00109	-0.00450	-0.00253	-0.0306**	-0.0699
	(0.0223)	(0.0175)	(0.0111)	(0.0140)	(0.0105)	(0.0140)	(0.0134)	(0.0106)	(0.0432)
Sales Growth (lag)	0.0164	0.0343**	0.0387***	0.0355***	0.0284**	0.0292**	0.0203	0.00125	-0.0314
	(0.0194)	(0.0130)	(0.0105)	(0.00880)	(0.0107)	(0.0112)	(0.0142)	(0.0125)	(0.0173)
Interaction	0.140	0.0465	0.0248	-0.0197	-0.0231	-0.0324	-0.0758	-0.00654	-0.0589
	(0.124)	(0.100)	(0.0674)	(0.0793)	(0.0766)	(0.108)	(0.113)	(0.112)	(0.274)
Age	0.0164	0.00535	0.00439	-0.000875	-0.00563	-0.00921***	-0.0145***	-0.0224***	-0.0222**
	(0.00897)	(0.00442)	(0.00356)	(0.00374)	(0.00291)	(0.00264)	(0.00336)	(0.00403)	(0.00852)
Size (lag)	0.0254***	0.0160***	0.0115***	0.00808***	0.00621***	0.00469***	0.00258	0.00509*	0.00491
	(0.00321)	(0.00208)	(0.00184)	(0.00167)	(0.00164)	(0.00126)	(0.00177)	(0.00202)	(0.00308)
Productivity (lag)	0.0144	0.0140**	0.00748*	0.00483	0.000828	-0.00178	-0.00440	-0.0163***	-0.0261***
	(0.00889)	(0.00532)	(0.00359)	(0.00322)	(0.00306)	(0.00321)	(0.00369)	(0.00395)	(0.00663)
R&D intensity (lag)	0.0707	0.121	0.216	0.233*	0.345***	0.410***	0.517***	0.727***	0.763***
	(0.134)	(0.123)	(0.116)	(0.0958)	(0.0929)	(0.0957)	(0.116)	(0.112)	(0.222)
Constant	-0.639***	-0.448***	-0.299***	-0.189***	-0.0881**	-0.00489	0.0875*	0.285***	0.459***
	(0.0804)	(0.0484)	(0.0350)	(0.0298)	(0.0297)	(0.0308)	(0.0349)	(0.0424)	(0.0597)
Observations	10447	10447	10447	10447	10447	10447	10447	10447	10447

Notes: Simultaneous quantile regression estimates of Equation (4). Bootstrap standard errors in parenthesis (100 replications). Asterisks denote significance levels: *p<0.05, ** p<0.01, *** p<0.001.