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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

It is often argued that persistent innovators are in a better position to outperform competitors, due to superior ability to sustain comparative advantages over time. In this work we exploit a long-in-time panel of Spanish manufacturing firms over the period 1990-2012 to examine the long-run contribution of innovation persistence to sales market shares and dynamics. We examine two main research questions. First, do persistent innovators grow more than other firms? Second, do persistent innovators show more persistence than other firms in their growth patterns over time? 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. The results are robust across different definitions of persistent innovators, according to persistence in R&D, product or process innovation, and patenting behaviour.

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

Persistence of innovation, broadly intended as the degree of inter-temporal continuity in the innovative behavior and success of firms, has been a central research topic for quite a long time, in view of the far-reaching implications for theory as well as for public policy.

Theoretically, from a more macro perspective, innovation persistence corroborates endogenous growth models and evolutionary-Schumpeterian accounts of aggregate growth postulating that sustained long-run growth eventually stems from the constant accumulation of new and economically valuable knowledge – from 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 Romer (1986, 1990) new growth theory. At a more meso, industry-wide level, innovation persistence provides support to explanations of industry dynamics identifying the process of creative accumulation by incumbent firms as the fundamental driver of innovation and growth, at the same time downplaying the beneficial effect of creative destruction dynamics usually attached to the activity of young entrants (i.e., distinguishing between Schumpeter Mark I vs. Mark II industry regimes, Malerba and Orsenigo 1995, 1996). At a more micro-level, moreover, innovation persistence constitutes a theoretically fundamental source of long-run competitive advantage of firms (due to cumulativeness and increasing returns in knowledge dynamics) and the persistently different ability to innovate is advocated as a convincing explanation for the observed wide and persistent heterogeneities in structure and performances across firms (Geroski et al., 1997), also in relation to technological trajectories and regimes (Dosi, 2007; Dosi and Nelson, 2010).

From a policy perspective, innovation persistence is crucial for the design of the interventions targeting innovation and growth, and to some extent for the inner justification of innovation policies. In fact, if persistent innovators represent the main driver of growth, then policies nurturing occasional innovators or potential "first-time" innovators – such as start-ups and new entrants – cannot be expected to effectively promote long-run economic development. More generally, public support to innovative firms may have more hope to deliver long-run effects on the economy if current innovation affects future innovation, i.e. if innovation dynamics is persistent.

Because of the so deep implications, a large stream of literature within the Economics of Innovation examines the extent of persistence in innovation activities and the possible mechanisms underlying its emergence. Empirically, we now know that different types of innovation activities – technological (i.e., R&D, product and process innovations, patenting) as well as non-technological (marketing and organization innovation) – exhibit different degrees of persistence. These heterogeneities have been explained through a number of theoretical lenses, reflecting different views on the modes and the determinants of the process of knowledge accumulation. In spite of their differences, all these theories of innovation persistence share that persistent innovators enjoy large and persistent competitive advantages, in turn providing them with a superior ability than other firms to grow and succeed in the market, especially over the long run (Section 2.1 provides a brief review of this literature).

In this paper we contribute to the literature by providing an empirical investigation of the long-run contribution of innovation persistence to firm growth trajectories, in general, and to patterns of sales growth and market share dynamics in particular. We take advantage of a long-in time panel of Spanish manufacturing firms covering the years 1990-2012, and address two main research questions: (I) Do persistent innovators grow more than other firms in terms of sales, on average, such that we can identify a positive "growth premium" attached to innovation persistence? (II) Do persistent innovators display more persistence than other firms in their sales growth dynamics, such that we can identify a "growth persistence premium" attached to innovation persistence?

In fact, despite the strong theoretical agreement among innovation scholars that innovation persistence foster market success, the Industrial Economics literature studying firm growth and the innovation-firm growth nexus (see extensive reviews in Coad, 2009; Audretsch et al., 2014) raise theoretical and empirical challenges to the notion that persistent innovators invariably outperform other firms. Empirically, there is mixed evidence about the effect of innovation on growth of the average firm (Bottazzi et al., 2001; Coad and Rao, 2008), while innovation is seemingly more beneficial to the growth trajectories of high-growth firms in the top quantiles of the growth rates distribution (see Freel, 2000; Coad and Rao, 2008; Hölzl, 2009; Falk, 2012). However, the role of this set of firms in spurring innovation and growth is highly debated (Daunfeldt et al., 2016): the strength of the innovation-growth relation varies depending on the innovation proxy (see Bianchini et al., 2018a) and, moreover, innovation activities does not help high-growth firms to replicate their high-growth records over time (Bianchini et al., 2017; Moschella et al., 2018). Such difficulties in establishing strong relations between innovative efforts and sales growth represent a puzzle, if evaluated through the lenses of theoretical models of firm-industry dynamics (even from competing schools, e.g. in evolutionary models as Dosi et al. 1995 vs. neoclassical equilibrium models as in Jovanovic 1982; Ericson and Pakes 1995). Indeed, all these frameworks present innovation represent as a key determinant of productivity differentials across heterogeneous firms, in turn driving the process of selection and reallocation of market shares towards more productive firms at the expenses of less efficient ones. The explanations proposed to interpret the weak role of innovation in sales growth dynamics resort to the uncertain, complex, boundedly-rational, firm-specific nature of the innovation processes, as suggested by broadly-defined capability-based or resource-based views of the firm. A related explanation, similarly rooted into recognizing the heterogeneities and idiosyncratic specificities across firms as a fundamental driver of performance, refer to the notion that firm growth is well approximated by an erratic, difficult to predict random process (Geroski, 2002), in fact well in tune with economics and strategic management theories of luck as a key determinant of firm performance (see Alchian, 1950; Barney, 1986, 1997; Denrell, 2004).

We add to the literature on the innovation-firm growth linkages by examining whether innovation persistence, rather than innovation levels or intensity per se, may turn out as a powerful determinant of sales growth and market share dynamics. In this literature, in fact, the attention towards the role of innovation persistence is very recent. Some studies investigate the link between innovation persistence and employment growth, whereas we focus here on sales dynamics as a genuine proxy of success in the market, thus directly related to the outcome that theories of innovation persistence predict to distinguish persistent innovators vis a vis other firms. The few works which focus, as we do, on sales growth address the role of innovation persistence in mediating the relation between growth and R&D, but do not systematically address the perhaps more fundamental research questions we tackle in this work (we review these limited literature in Section 2.2).

Beyond examining our main research questions, our work contribute to the existing literature under several respects.

First, we consider the heterogeneities that may characterize the ability to persistently undertake different types of technological innovation. In fact, we distinguish four groups of persistent innovators, according to persistence in R&D activities, in patenting behavior, and in the introduction of new products or new processes. We are, thus, able to raise the further interesting question, not yet systematically explored, whether persistence in innovation inputs, intermediate or final outputs are all alike in delivering differential sales growth premia vis a vis other firms.

Second, differently from the few existing studies, we frame our empirical 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, controlling for possibly relevant firm attributes. Together with allowing us to estimate the long-run consequences of innovation persistence, our empirical strategy tackles in a simple way the possible joint determination between our outcome variables and innovation persistence. Success on the market, in fact, represents an obvious source of those financial resources that may enable firms to keep innovating over time. By measuring innovation persistence and growth dynamics over two non-overlapping time periods, we are more confident than in previous studies to break the implicit reverse causality.

Third, and relatedly, by having at our disposal 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 innovation decisions of firms over a relatively long time horizon. Most of the existing studies of innovation persistence, by relying upon innovation surveys (such as the European CIS), have only partial information on these patterns. In fact, 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).

Our main findings, in short, provide a negative result: as compared to other firms, firms that persistently innovate over the first decade, do not grow more and do not display differences in sales growth persistence over the subsequent years, independently from whether persistent innovators are identified according to product or process innovation, patenting behavior, or R&D activity. This is in sharp contrast with theories of innovation persistence and with models explaining industry dynamics in terms of reallocation of market shares in favor of the more competitive, persistently innovative firms. Conversely, our results provide support to random or luck theories of firm growth, stressing the inherently unpredictable nature of firm growth patterns. Idiosyncratic and erratic components of sales growth dynamics prevail over XXX the supposedly strong relation linking innovation persistence and success in the market.XXX

2 Background literature and framework

We here provide a review of the literature on innovation persistence and present the few papers addressing whether the latter affects firm growth trajectories. We then use this review to develop an interpretative framework useful to guide our empirical analysis.

2.1 Innovation persistence: facts and theories

The starting point of our work is the bulk of innovation studies addressing extent and causes of persistence in technological innovation.

On the empirical side, as well documented in a recent review by Le Bas and Scellato (2014), this literature provides quite heterogeneous results, not always comparable across works, due differences in the characteristics of data (surveys like CIS or similar sources, vs. other sources), type of technological innovation dimension considered (e.g., inputs vs. outputs), and methodologies adopted to measure persistence (e.g, based on duration models, length of innovation spells, transition probabilities).

In brief, we can distinguish three main sets of results.[1] A first emerging fact is that the extent of innovation persistence considerably varies with the length of the time span available in the data. Indeed, the longer the time span considered to measure innovation persistence, and the smaller the cluster of firms expected to innovate frequently enough to qualify as persistent innovators.

Second, there is heterogeneity in the degree of innovation persistence according the type of technological innovation considered, i.e. according to innovation inputs (R&D), innovation outputs (products and processes) or intermediate outputs (such as patents). In fact, the evidence supports a clear ranking in the extent of innovation persistence, with patents exhibiting low persistence, while R&D and output measures are usually found to be more cumulative. This ranking, however, ought to be read together with the consideration that different technological innovations have a different likelihood to be repeatedly undertaken by firms over time, by their nature. Patents and product innovation are regarded as "'strong measures" of innovation persistence since the inherently more costly, complex and time-consuming processes underlying

[1] For more detailed surveys, see also Fontana and Vezzulli (2016), and the exhaustive reviews in Ganter and Hecker (2013) and in Tavassoli and Karlsson (2015). The last two articles also provide excellent reviews of theory and evidence about persistence of non-technological innovation, which we do not discuss here.

these two activities makes it a priori more difficult to find persistence, as opposed to R&D and process innovation, which are, thus,considered as "weak measures" (Le Bas and Scellato, 2014). The available studies confirm 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.

Third, several firm-level characteristics and contextual factors are found to interact with innovation persistence. The degree of persistence in fact differs in place, time, industries, and according to technologies. This relates also to the debate about spurious vs. true state dependence (see Tavassoli and Karlsson, 2015; Raymond et al., 2010), i.e. concerning the extent to which subsequent innovation depends purely from past innovation, or rather from other performances and factors jointly evolving with innovation itself. The general implication is a strong case in favor of including several controls in estimating the possible impacts of innovation persistence on firm performance, in order to break potential co-determination between innovation persistence and a number of firm-level factors.

On the theoretical side, the emergence of innovation persistence is understood as the result of cumulative knowledge patterns, characterised by increasing returns and path or past dependence in learning dynamics. Within this broad view, a number of conceptual frameworks can be traced, offering several explanations of the mechanisms underlying innovation persistence. The classical Schumpeterian interpretation points to the market structure and, in particular, to the role of incumbent, typically larger 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 disruption and low innovation persistence characterize 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. In a related framework, the success-breeds-success hypothesis is that firms succeeding in innovating will be those able to also achieve above-the-average profits, and, thus, to accumulate the resources needed to further innovate (Cefis and Orsenigo, 2001; Cefis, 2003; Cefis and Ciccarelli, 2005). Complementary to this view, the resource constraints perspective (dating back to Phillips, 1971), stresses that a record of previously successful innovations also helps easing access to external resources. Lastly, the sunk-costs explanation (Sutton, 1991; Manez et al., 2009) highlights the irrecoverable nature of innovative investment, implying that persistent innovation patterns emerge due to firms developing technological competitiveness strategies heavily sourcing from past and path dependent knowledge accumulation and internal capabilities (Antonelli et al., 2013).

While these different frameworks predict innovation persistence to emerge no matter which specific type of technological innovation (inputs or outputs) is in question, they imply different predictions about whether one type of technological innovation or another may exhibit more persistence (Tavassoli and Karlsson, 2015). High persistence in R&D is a common tenet in essentially all theories, since R&D is invariably understood as the basic mode of knowledge creation and accumulation: feed-backs from past non-exhaustible knowledge and piling up of knowledge stock implies for firms already engaged in R&D to be more able than other firms to create new knowledge exploiting dynamic scale economies. The degree of persistence in product and process innovation is generally predicted to follow (and thus to be similar to) the degree of persistence observed in R&D, since R&D represent in all the different frameworks the basic input source of the knowledge necessary to lead to both types of innovation outputs. However, there are also theoretical arguments supporting that process innovation would exhibit less cumulative and persistent dynamics than product innovation. In fact, the sunk cost argument applies less to process innovation, since many new processes do not result from specific and intense R&D investment, but rather from shopping from outside the specific machineries (or an entirely new factory) that can be used to change production processes (Ganter and Hecker, 2013; Tavassoli and Karlsson, 2015). Lastly, patenting activity is expected to exhibit lower persistence. Patenting is in fact recognized as subject to little dynamic scale economies, strongly varying across countries and by technologies (Ganter and Hecker, 2013; Fontana and Vezzulli, 2016), and threshold effects have been identified such that persistence in patenting becomes substantial only after a certain number of previous patents have been cumulated (Geroski et al., 1997; Cefis and Orsenigo, 2001; Cefis, 2003). This ranking in the degree of persistence across technological innovations broadly maps into the empirical finding reviewed above.

2.2 Innovation persistence and firm growth

As mentioned in the introduction, despite the large literature examining the innovation-firm growth nexus, very few papers relates innovation persistence to patterns of firm growth.

Growing attention is testified by recent works focusing on growth in terms of employment. Notably, the two existing studies we are aware of both exploit the same long-in time panel of Spanish firms that we use in this study. Triguero et al. (2014) ask whether subsequent employment creation is influenced by product and process innovation measured at different time-lags back in time. Their findings show that product innovation does not have any effect, while process innovation positively affect employment dynamics, for SMEs in particular. Bianchini and Pellegrino (2017) pose very similar research questions to those we pose here, studying whether innovation persistence affects average and persistence of employment growth. Their results, somewhat in contrast to Triguero et al. (2014), show that process innovation persistence does not play any role, whereas product innovation persistence associates with higher employment growth and with an higher probability that firms enjoy relatively long spells of job creation.

Although interesting, these works speak to a parallel literature studying the compensation mechanisms underlying the labour-saving vs. labour-augmenting effects of different innovation activities.[2] Our work is more closely related to the few studies that consider the effect of innovation persistence on the dynamics of sales growth. Sales and employment do not provide interchangeable measures of size evolution, in fact. Employment dynamics strongly depends from labour market regulation and choices related to human capital accumulation of firms, whereas we focus here on whether innovation persistence affects patterns of success on the market.

To our knowledge, only two published articles address the contribution of innovation persistence to sales growth and market share dynamics. Demirel and Mazzucato (2012) take a long-run perspective similar to our study, analyzing US listed pharmaceutical companies from COMPUSTAT data over the period 1950-2008. The analysis only examines the effect of persistence in patenting, given the known importance of patents in bio-pharma, with patent filing rates skyrocketing in the last 15-20 years, also due to increasing use of strategic patenting. Besides other results, they show that persistent patenting has an at least indirect effect on sales dynamics, working as a pre-condition for R&D to positively impact subsequent growth of sales. The work by Deschryver (2014) examines a similar question, asking to what extent the ability to persistently introduce new products or processes shapes the relation between R&D and sales growth, but focusing on the role of persistence in product and process innovation. The findings, based on a panel of Finnish firms observed over the period 1998-2008, show that R&D contributes to sales growth more strongly in firms that continuously innovate in both types of innovative outputs than it does for occasional innovators.

2.3 Hypotheses

What are, then, the relations to be expected from theory and previous empirical studies between the ability to persistently engage into innovative activities 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 other firms in terms of our two main research question about (I) average sales growth performance and (II) persistence in sales growth patterns ?

Contrasting predictions emerge from existing literature. On the one hand, all theories explaining the emergence and the mechanisms of innovation persistence, corroborated by models of market shares reallocation across heterogeneously efficient firms, share that innovation persistence is key to establish and sustain competitive advantage over time. The continuous accumulation of knowledge trough persistently performing R&D, the ability to continuously transform new ideas to patentable and/or economically successful products, as well as efficiency advantages from continuously adopting innovative processes, represent structural characteristics that make persistent innovators more apt than other firms, almost by definition, to compete and succeed in the market, and to self-sustain their strong competitive advantage over time.

As a result, one would expect to find a positive answer to both our research questions. Firms identified as persistent innovators in the first 10 years of the data are expected to grow more

[2] Vivarelli (2014) and Calvino and Virgillito (2017) provide exhaustive surveys for the interested readers.

and to exhibit more persistent sales growth dynamics than other firms in the following years, thus enjoying a positive "growth premium" and a positive "growth persistence premium".

Towards an opposite hypothesis point, on the other hand, the predictions that one could derive from broadly defined theories of growth as a random process guided by idiosyncratic firm specificities or by luck, originating within capability or resource-based views of the firm and stressing the difficult to predict nature of the patterns of innovation and growth performance. This group of theories offer strong justification to consider the emergence of positive growth premia for persistent innovators far less obvious. In fact, the unpredictability and random nature of growth patterns postulated by these frameworks imply zero correlation between sales growth dynamics and innovation persistence, and thus zero "growth premia" and zero "growth-persistence premia" for persistent innovators.

Another aspect we address in the empirics, but for which there is less clearcut guidance from theory, is about whether the growth premia possibly accruing to persistent innovators vary according to persistence in the different types of technological innovation we consider. Theories of innovation persistence do envisage that different technological activities may in fact display different degrees of persistence, but they are silent about the implications for growth patterns.

We resort to economic intuition on the heterogeneities characterizing the innovation-growth nexus to inform our predictions. The very distinction between innovation inputs vs. innovation (intermediate or final) outputs implies that R&D, patents, and product or process innovation represent dimensions of the innovation process that differently relates with firm performance, primarily with productivity, but also with sales and market shares dynamics (e.g., in a knowledge production function framework Griliches, 1979, 1995; Crepon et al., 1998). We expect a precise ranking, in fact, with R&D and process innovation having weaker effects as compared to product innovation and patents (Goedhuys and Veugelers, 2012; Bianchini et al., 2018a). First, although R&D is the primer source of knowledge accumulation, and often a precondition to innovate in processes and products, the ability of R&D to spur growth in the market is strongly mediated by the uncertainties of R&D outcomes as well as by the time-lags needed for R&D to engender new sales. Second, according to the classical interpretation that new processes are implemented primarily to reduce costs, process innovation is likely to have only indirect effects on sales growth, only to the extent that efficiency and price competition are the main drivers of market share reallocation across firms (and recent empirical findings call into question that competitive selection works strongly as expected, see Bottazzi et al., 2010; Dosi et al., 2015). Conversely, product innovations and patents are generally regarded as having a stronger, positive link with sales growth. After all, new patents and new products obviously provide firms with the more direct means to achieve growth in the market (Hay and Kamshad, 1994; Cohen, 2010), as compared to the other dimensions of innovation we consider in this work.

We assume these arguments to also apply when considering how persistence in innovation activities, rather than innovation levels or intensity, relate to sales growth dynamics. Indeed, the uncertainties characterizing R&D outcomes hampers the immediate translation of new knowledge accumulated through R&D into new discoveries, new products and new revenues, thus making the relation between persistence in R&D and firm growth relatively nuanced. A continuous, persistent stream of 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. Instead, firms that succeed in continuously introducing new products or patents are in a better position to keep some degree of monopoly in markets or niches, escape erosion of sales and market share due to potential imitation or product out-dating, and more likely to enjoy a stream of profits that can be used to sustain further growth.

On these grounds, we expect that if any growth premia from innovation persistence ought to emerge, then persistence in R&D and process innovation are both less beneficial to sales growth than persistently innovating in products or filing for new patents. Thus, concerning our first research question, positive and larger "growth premium" are more likely to manifest for persistent product innovators and persistently patenting firms, than for firms that persistently perform R&D or process innovation.

Similarly, we also foresee a certain degree of heterogeneity across innovation persistence indicators also with respect to our second research questions, pertaining growth-persistence premia. Our intuition is that companies persistently translating their knowledge accumulation into marketable innovations (products or patents) are also those more likely to preserve a superior competitive advantage over time, due to the closer association of patents and products with "innovation-driven" market success, as opposed to firms that show R&D or process innovation persistence. Thus, we expect positive and larger "growth persistence premium" to emerge for firms that persistently introduce new products or persistently file for new patents than firms that persistently engage in R&D or process innovation. Whether these growth-persistence premia are strong enough to counter balance the highly unpredictable, erratic and seemingly luck-driven patterns of growth over time suggested by studies of sales dynamics, is an empirical question that our analysis contributes to shed light on.

3 Data, main variables and descriptive statistics

3.1 Data sources

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. 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.

Firms are submitted each year 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.[3]

The dataset is proprietary, and we accessed through a specific research agreement to a subset of variables for a total of 3193 firms that we can follow over the period 1990-2012. In this working sample, we have information about different types of innovation activities, that we exploit to identify persistent innovators, as well as a set of firm-level characteristics that allow to track growth patterns and other attributes to be used as control variables in our analysis.

3.2 Identifying persistent innovators

According to our hypotheses, we want to analyse how sales growth trajectories relates to persistence in four different types of technological innovation: R&D, patenting, product and process innovation. In the subset of the ESEE dataset available to us, these dimensions of innovation are measured as follows, for each firm and each year: total expenses in R&D during the year; two dummy indicators taking value one if a firm has introduced new products or new processes in the year; and the total number of new patents filed during the year (applications filed either in Spain or abroad).[4] The availability of this time-varying information is the starting point to identify persistent innovators and other firms over the initial decade 1990-1999, and then contrast the long-run growth performance of the two groups over the following period 2000-2012.

No clearcut and commonly accepted criterion exists in the literature for the empirical identification of persistent innovators. Existing studies that focus on quantifying the degree of innovation persistence adopt several different notions of persistence, such as length of innovation spells, degree of autocorrelation of innovation variables, or transition probabilities in and out percentiles of innovation variables distribution. While these studies deliver a rich picture, none of these approaches offers an operational definition of 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 is

[3]For further details on the characteristics of the ESEE dataset, see Jaumandreu and Farinas (1999).

[4]The definition of R&D, product innovation and process innovation comply with international standards (according to the Oslo manual). Concerning product innovation we cannot distinguish, contrary to other innovation surveys, if new products are new-to-the-market or only new-to-the-firm.

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.

confronted with a number of practical issues, also related to the characteristics of the available data. One choice could be, for instance, to define as persistent innovators only those firms performing a given innovation activity in all the years over the period of observation. But one could also reasonably opt to consider as persistent innovators firms that present long spells of consecutive years of innovation, although with some year-gaps in between two innovation spells. In the latter case, one also faces several open choices regarding how many years of consecutive engaging in a given innovation activity should be considered enough to qualify a firm as persistently innovating.

In our empirical setting, having the 10 years of data over the period 1990-1999 to identify persistent innovators, an arguably unquestionable definition of persistent innovator would be that of a firm that performs a given innovation activity in all the years 1990-1999. No firms verify this stringent criterion in our data, however. A clear trade-off emerges between including only firms that innovate consecutively over relatively many years, 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.

We experimented with less stringent criteria, focusing on spells of consecutive innovation of different length, and eventually define as persistent innovators those firms performing a given innovative activity for at least 7 consecutive years, out of the 10 years spanning the period 1990-1999. This strategy surely allows to identify firms that do not innovate only occasionally over the considered period. With this criterion, indeed, we substantially discard 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.

We build four groups of persistent innovators, by applying our identification criterion separately to each of the four innovation activities considered (non-zero R&D expenditures, product and process innovation, newly filed patents). Table 1 reports the number of persistent innovators by innovation indicator, as 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. 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

Table 2: Pairwise correlations between innovation persistence indicators

	R&D Persistent	Prod. Innov. Persistent	Proc. Innov Persistent	Patent Persistent
Persistent in R&D	1.0000			
Persistent in Prod. Innov.	0.4242*	1.0000		
Persistent in Proc. Innov.	0.3366*	0.2670*	1.0000	
Persistent in Patenting	0.2491*	0.2243*	0.1698*	1.0000

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

R&D (about 10% of the total), and similar figures (358 firms, a share of about 11%) emerge for firms that persistently carry out process innovation. Persistent product innovators are remarkably less frequent (100 firms, about 3.5% of the total), while firms persistently patenting stand out as the least populated group (35 firms, a 1% share). This heterogeneity in the frequency of the different persistent innovators categories is well in tune with previous studies highlighting that different innovation proxies deliver weak vs. strong measures of innovation persistence.

Table 2 reports pairwise correlations between the four innovation persistence indicators, as a way to appreciate the degree of overlapping between 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: persistent innovators with respect to one innovation dimension are not very likely to be persistent innovators 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.[5]

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.

3.3 Firm growth and firm characteristics

To capture patterns of success in the market, we consider firm growth in terms of sales. Following other studies in firm growth empirics, we define our outcome variable as the log-difference

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

[5]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.

where s_{it} is the log of annual sales S of firm i in year t, normalized by the sectoral average of (log-)sales in the same industry wherein firm i belongs to

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

The normalization is performed by 2-digit industries (EUROSTAT-NACE classification, Rev.2), which is the sectoral disaggregation available in ESEE. This transformation of sales implies that our growth measure G captures the dynamics of success on the market in terms of relative sales expansion over time. 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.[6]

Concerning other firms attributes, in the subset of the ESEE data available to us we have access to a standard set of firm characteristics usually employed as control variables in firm growth empirics. First, we can include proxies of 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 control variable for firm size, since sales already enter in the definition of the outcome variable G. Further, we can include in the analysis a measure of labour productivity, defined as value added per hour worked (*Productivity*). This is justified on the theoretical grounds that efficiency is positively associated with the ability to gain market shares (despite some recent empirical investigations suggest that market selection based on productivity may actually be weak, see Bottazzi et al., 2010; Dosi et al., 2015). Lastly, we can also consider a measure of the intensity of R&D, defined as annual R&D expenditures per unit of output (*R&D intensity*). The relation between the latter and sales growth is difficult to predict, given uncertainty of R&D outcomes. We consider this variable as a measure of overall innovative efforts of firms over the years where we track growth patterns, after that we have categorized firms as persistent innovators vs. other firms based on their innovative behavior in the previous decade.

Table 3 shows basic descriptive statistics of sales growth G and firm characteristics, computed pooling data over the period 2000-2012, distinguishing by persistent innovators and other firms. Since all the variables are known to be skewed, we report the median which is more informative than the mean about central location.

Persistent innovators, however defined, generally display higher median growth rates than other firms, although this difference is relatively small for persistent innovators as identified by R&D, product and process innovation behavior, and clearly marked only for persistently patenting firms. Moreover, comparatively to other firms, persistent innovators clearly appear as larger, older, more productive and relatively more R&D intense. This pattern generally holds no matter the innovation persistence indicator considered, although the median value of R&D intensity is identical across persistent process innovators and other firms. The reported standard deviations, all much higher than the median in most cases, confirm wide heterogeneities within

[6]We implemented a basic cleaning of outliers excluding 6 firm-year observations with $G_{i,t} > 5$ or $G_{i,t} < -5$.

Table 3: Sales growth and firm attributes - Descriptive statistics

		R&D Persistent	Prod. Innov. Persistent	Proc. Innov Persistent	Patent Persistent	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 G as defined in Eq. (1); Age is measured in years from foundation; Size is number of employees; Productivity is (log) Euros per hour worked; R&D intensity is the ratio of R&D expenses over total sales.

and across all groups of firms. Kernel estimates of the unconditional empirical distribution of G and firm attributes, as shown in Appendix A, confirm that persistent innovators do not exhibit marked differences in growth rates, and are comparatively larger, older, and generally more productive and more R&D intense. Nonetheless, wide support of empirical densities also show that relatively small, young, low productivity or low R&D intense firms are also present among persistent innovators.

4 Baseline analysis and results

We next turn to address our research hypotheses, asking whether firms identified as persistent innovators over the period 1990-99 grow more and more persistently than the other firms over the following years 2000-2012. In this section we present our baseline regression framework and results, also comparing the findings across the different indicators of innovation persistence. Extensions of the analysis are next presented in Section 5.

4.1 Innovation persistence and firm growth

To address our first research hypothesis, we compare average growth across persistent innovators and other firms via the following regression model

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

where the subscript it stands for the firm-year pair running over the years 2000-2012, G_{it} is 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. The omission of the time subscript t underlines that persistent innovator status is time-invariant over the years defining the regression period. Separate regressions are run alternatively including the four PERS dummies based on R&D

Table 4: Innovation persistence and firm growth - Main Estimates

	R&D PERS	**PROCESS PERS**	**PRODUCT PERS**	**PATENT PERS**
PERS dummy	-0.00900	-0.00667	0.0146	-0.00390
	(0.00797)	(0.00664)	(0.0112)	(0.0147)
Age	0.00473	0.0169	0.00640	0.0560
	(0.00640)	(0.0123)	(0.00940)	(0.0291)
Size (lag)	0.0377***	0.0463***	0.0452**	0.0225***
	(0.00777)	(0.0136)	(0.0143)	(0.00327)
Productivity (lag)	-0.0379***	-0.0450***	-0.0457***	-0.0539***
	(0.00831)	(0.0116)	(0.0104)	(0.0144)
R&D intensity (lag)	1.109***	1.088***	1.039***	0.999***
	(0.201)	(0.208)	(0.232)	(0.205)
P-score	-0.177**	-0.417*	-0.573*	-1.002**
	(0.0633)	(0.187)	(0.284)	(0.431)
Constant	0.158*	0.197*	0.218**	0.260***
	(0.0651)	(0.0836)	(0.0729)	(0.0948)
Observations	11693	11693	11693	11693

Notes: OLS estimates of Equation (3). All specifications also include year and sector fixed effects. Bootstrap standard errors (100 replications) in parenthesis below the coefficients. Asterisks denote significance levels: * p<0.05, ** p<0.01, *** p<0.001.

expenses, product or process innovation, and patenting. In all models, the control set X encompasses the firm-level characteristics presented above (age, size, productivity and R&D intensity), all lagged to at least partially account for possible simultaneity, and we also include a full set of sector (2-digit) and year fixed-effects.

The coefficient of primary interest is β_1, capturing the possible "growth premium" for persistent innovators, conditional on the covariates. Our strategy to divide the sample into two sub-periods should considerably break endogenous joint determination of growth patterns and innovation persistence. In fact, the construction of the PERS dummies does not exploit the years considered in the regression analysis. A simple OLS estimate of β_1 may suffer from a residual bias, however, to the extent that observed and unobserved firm characteristics that affect assignment into 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 a two-steps procedure. As a preliminary step, we use the data in the first sub-period 1990-1999 to estimate, for each firm, a predicted probability (propensity score) to belong to each group of persistent innovators. This is operationalized with Probit models where innovation persistent status PERS (separately for each innovation dimension) is regressed against firm-level controls included in the main equations (age, size, R&D intensity and productivity), plus intangible assets per employee as an additional measure to capture generic innovation not accounted for by R&D in the first period. Since PERS status does not vary over time, the firs-step Probits take as regressors the within-firm time-series averages of firm characteristics. Next, in the second step, the propensity scores (henceforth p-scores) from the first-step Probits are included as an additional regressor in an OLS estimate of the main Equation (3) performed on the data over the period 2000-2012. Adding p-scores we can be more sure that the PERS categories are assigned as good as random, *conditional on controls measured over the estimation period 2000-2012*.[7]

Table 4 shows the results of the separate regressions alternatively including the four different innovation persistence indicators. The estimates deliver a consistent picture: we do not find evidence of a statistically significant difference in the average growth of persistent innovators vis a vis other firms. The result is robust across the different groups of persistent innovators.

The patterns featuring control variables coefficients are robust across the different specifications. Size and R&D intensity both have a positive association with subsequent growth, whereas Age does not, and the coefficients on lagged productivity reveal negative correlation. Of course, these patterns should not be overemphasized, since controls may be partially endogenous, and just serve here to account for omitted components that may otherwise bias the coefficients on the PERS dummies.

4.2 Persistence of innovation and persistence of firm growth

To address our hypotheses on the effects of innovation persistence on persistence of sales growth, as a baseline exercise we investigate the autoregressive structure of growth patterns. We specify the following regression equation

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

In this specification, relative sales growth G, the PERS dummies and the controls set X are defined as in Equation (3) above, while 1-year lagged growth G_{it-1} accounts for growth persistence, and we interact the latter with the PERS dummies to model the difference in growth persistence associated to persistent innovator status. The coefficient α_3 is the coefficient of main interest, yielding an estimate of the average "growth persistence premium" for persistent innovators, conditional on controls (age, size, productivity, and R&D intensity, plus sector and year fixed-effects). The estimation strategy parallels the estimation procedure designed to estimate growth-premia in Equation (3). We perform separate regressions alternatively including the four PERS indicators (in terms of R&D, product or process innovation and patenting behavior), and cure for residual endogenous determination of each PERS dummy via first-step Probit p-scores for persistent innovator status, generated as explained above.

The results are presented in Table 5. 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, no matter the definition of PERS status considered.

[7]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 5: Innovation persistence and persistence of firm growth - Main Estimates

	R&D PERS	**PROCESS PERS**	**PRODUCT PERS**	**PATENT PERS**
PERS dummy	-0.00813	-0.00339	0.0157	-0.000650
	(0.00871)	(0.00788)	(0.0109)	(0.0178)
Sales Growth (lag)	-0.0199	-0.0191	-0.0309	-0.0211
	(0.0194)	(0.0195)	(0.0205)	(0.0245)
Interaction	-0.0501	-0.0435	0.0227	-0.0756
	(0.0620)	(0.0602)	(0.0619)	(0.148)
Age	0.00819	0.0230	0.00942	0.0649*
	(0.00798)	(0.0134)	(0.00951)	(0.0280)
Size (lag)	0.0452***	0.0544***	0.0527***	0.0236***
	(0.00723)	(0.0137)	(0.0132)	(0.00303)
Productivity (lag)	-0.0374***	-0.0461***	-0.0463***	-0.0543***
	(0.00789)	(0.0111)	(0.0103)	(0.0124)
R&D intensity (lag)	1.202***	1.153***	1.094***	1.005***
	(0.204)	(0.225)	(0.211)	(0.192)
P-score	-0.240***	-0.528**	-0.715**	-1.109**
	(0.0624)	(0.183)	(0.269)	(0.415)
Constant	0.131	0.181*	0.204**	0.245**
	(0.0685)	(0.0758)	(0.0675)	(0.0767)
Observations	10246	10246	10246	10246

Notes: OLS estimates of Equation (4). All specifications also include year and sector fixed effects. Bootstrap standard errors (100 replications) in parenthesis below the coefficients. Asterisks denote significance levels: * p<0.05, ** p<0.01, *** p<0.001.

Coefficient estimates on the controls tend to replicate the patterns emerged from the growth-premia regressions. Conditional on other factors, sales growth positively correlates with lagged size and R&D intensity, while we find negative association with lagged productivity and largely insignificant correlation with age.[8]

Overall, our baseline analysis shows that, contrary to our working hypotheses, persistent innovators do not differ from other firms in their "long-run" growth trajectories: on average at least, they do not grow more and do not exhibit more persistence. These results turned robust to a number of robustness checks, concerning identification of persistent innovators and modification of estimation strategy to further exploit the panel structure of the data. These additional analysis are reported in Appendix C.

5 Extended analysis

We next provide extensions of the analysis to consider the role of firm size, variation of results along the quantiles of the growth rates distribution and a different notion of growth persistence.

[8]These stable patterns on the control coefficients agree with a preliminary analysis of the pairwise correlations between the controls themselves. They are also in line with a preliminary OLS regression between the controls and sales growth, reassuring that these are in fact good controls. See Appendix B.

5.1 The role of firm size

A first interesting issue is whether our main results vary by firm size. Despite the literature recently started to recognize the role of small firms in innovation persistence (Corradini et al., 2016), large firms are especially likely to display innovation persistence, since persistence does not manifest in phases of creative destruction where small firms are expected to play a major role. Together, we also know, from firm-growth empirics, that larger usually display lower growth rates and more stable growth paths over time. In other words, size and innovation persistence may interact in shaping our main findings. The descriptive analysis (in Section 3.3) in fact support that persistent innovators are relatively larger than other firms, although (as kernel densities in Appendix A show) all groups of persistent innovators that we identify encompass small-medium as well as larger firms.

In the main analysis we account for possible size effects through including size among controls. But we can shed further light on the interaction between size and innovation persistence by 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.

Table 6 and Table 7 report the results. They support that the baseline findings do not stem from a sheer size effect. In the specification modeling the relation between persistent innovation and average growth (in Table 6), the coefficients on the PERS dummies are all insignificant, no matter the proxy of innovation persistence considered. Similarly, we do not find variation across size categories in the specification modeling growth-persistence premia (in Table 7): the estimated interaction coefficients are all statistically zero, once again across all the dimensions of innovation persistence.[9]

In sum, small-medium (large) persistent innovators do not grow more and do not show more persistent growth patterns than other small-medium (large) firms.

5.2 Asymmetries along firm growth quantiles

Further, we complement the baseline empirical analysis with a quantile regression exercise, allowing to explore the variation of coefficient estimates along the entire distribution of sales growth rates. This connects our work with the recent stream of empirical research finding that innovation is specifically relevant for high-growth firms in the top quantiles of the growth rates distribution, rather than on average growth. We add to previous studies in this literature by asking, for the first time to our knowledge, whether innovation persistence, rather than

[9]Our baseline findings were fully confirmed also in a further exercise where we re-estimated Equations (3) and (4) on the un-split full sample, but including size-squared as an additional regressor. Results are in Appendix D.

Table 6: 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 $\leq$ 250) and large firms (Large, employees $>$ 250). All specifications also include year and sector fixed effects. Bootstrap standard errors (100 replications) in parenthesis below the coefficients. Asterisks denote significance levels: * p<0.05, ** p<0.01, *** p<0.001.

Table 7: 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 ≤ 250) and large firms (Large, employees > 250). All specifications also include year and sector fixed effects. Bootstrap standard errors (100 replications) in parenthesis below the coefficients. Asterisks denote significance levels: * p<0.05, ** p<0.01, *** p<0.001.

innovation per se, has similarly asymmetric effects in the top vs. lower quantiles of growth rates.

We re-estimate our baseline specifications in Equation (3) and Equation (4) via conditional quantile regressions (Koenker and Bassett, 1978). However, we cannot include p-scores since, in fact, including p-scores would assume that innovation persistence propensity is constant across quantiles, which would be at odds with a genuine interest in quantile effects.[10]

In Table 8 and Table 9 we show the estimates of the coefficients of main interest.[11] In general, coefficient estimates do vary significantly along growth quantiles, allowing to observe some interesting pattern occurring in the tails that cannot be appreciated in the baseline OLS estimates.

More specifically regarding our first research hypothesis (see Table 8), we find some evidence of negative growth premia for persistent innovators in the upper quantiles, although negative growth premia are more robust for persistent R&D innovators (coefficients significant in most upper quantiles), while they display weaker significance and are confined to the very top quantiles for the other groups of persistent innovators. This finding at least partially reflects that persistent innovators are relatively less concentrated than other firms in the upper quantiles of sales growth, as suggested by unconditional distributional analysis (see Appendix A). Firm-size effects could play some role in this result, due to lower growth dispersion usually featuring large firms, but we cannot perform split-sample quantile regressions by firm size, since too few persistent innovators will in that case fall in most quantiles. Our identification, thus, exploits that both small and large firms are present in the four groups of persistent innovators, and we do in fact condition upon size.

The findings about growth persistence premia (in Table 9), instead, are quite consistent across different innovation persistence indicators. In all the specifications, the interactions 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.

5.3 Growth persistence as transition probabilities

Lastly, we explore to what extent our conclusion that persistent innovators do not enjoy "growth-persistence premia" depends from the notion of growth persistence that we used in the baseline analysis. In fact, first-order autocorrelation of growth rates, despite widely adopted in firm growth empirics, just delivers a rather specific definition of persistence. We experiment with a less restrictive notion based on transition probabilities across the quartiles of the growth rates distribution. As compared to the baseline analysis of autoregressive structures, we here provide complementary evidence on: (i) the degree of intertemporal mobility/persistence in the intra-distributional rankings of sales growth across persistent innovators and other firms,

[10]We thank an anonymous referee for pointing this out. Note also that we do not include sector fixed-effects in this analysis, since the number of persistent innovators per sector is too small to identify sector-specific intercepts in growth quantiles.

[11]Tables reporting the full set of coefficients are available upon request.

Table 8: 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). All specifications also include firm controls (Age, Size, Productivity, R&D intensity – coefficients unreported) and year fixed-effects. Bootstrap standard errors (100 replications) in parenthesis below the coefficients. Asterisks denote significance levels: *p<0.05, ** p<0.01, *** p<0.001.

Table 9: 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). All specifications also include firm controls (Age, Size, Productivity, R&D intensity – coefficients unreported) and year fixed-effects. Bootstrap standard errors (100 replications) in parenthesis below the coefficients. Asterisks denote significance levels: *p<0.05, ** p<0.01, *** p<0.001.

Table 10: Growth persistence premium, 3-years transitions across growth quartiles

			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.

going beyond the average “growth-persistence premia” revealed by regression models; and (ii) whether such mobility/persistence changes over time horizons longer than one year.

In Table 10 we show the 3-years transitions across quartiles of yearly growth rates distributions computed over all the firms over the period 2000-2012, and then distinguishing the estimated frequencies of change by persistent innovators and other firms. To ease interpretation of the degree of persistence characterising the matrices, we also report two summary measures of intra-distributional mobility, the Shorrocks’ index and the Bartholomew index.

We find that persistence is generally low, as the estimated transition probabilities all range in between 20% and 35%. More specifically, these relatively low frequencies are rather invariant across persistent innovators and other firms, independently from the indicator of innovation persistence considered. The mobility measures (Shorrock’s indexes mostly around or above

0.95, and Bartholomew's indexes in between 0.3 and 0.4.) support this conclusion.[12] Overall, we confirm that innovation persistence does not vary significantly across persistent innovators vs. other firms. We also performed the same analysis estimating 5-years transition matrices, finding consistent results (See Appendix D).

6 Conclusion

While a large literature studies the empirical relevance and the determinants of innovation persistence, there is limited empirical effort to link innovation persistence to patterns of sales growth and success in the market. This paper contributes to fill this empirical gap. Our analysis conveys a clear negative result: contrary to our working hypotheses, persistent innovators do not grow more on average and do not show more persistent growth paths than other firms populating the economy. The findings are invariant to measuring innovation persistence in terms of different dimensions of technological innovation (new products or processes, patenting behavior and R&D), and prove robust to a number of sensitivity analyses.

Our results bear implications for both academic research and policy. In terms of innovation studies, they are at odds with theories of innovation persistence, generally delivering a shared view that persistent innovators ought invariably out-compete other firms, both on average and constantly over time. We can advance two orders of explanations for this disagreement with the theory. First, our findings may be partly ascribed to various mechanisms that can undermine the otherwise strong relations between firm growth and the different dimensions (inputs vs output) of technological innovation we consider: (i) uncertainty and lag effects may cloud the contribution of persistent R&D to success on the market; (ii) persistent process innovations may display more direct effects on cost efficiency, only indirectly passing to growth in the market; (iii) persistence in patenting only imprecisely measure the ability to come up with new inventions of commercial value, e.g. because actually capturing strategic, anti-competitive behavior; (iv) constantly introducing new products may partly "cannibalize" sales growth coming from already existing products. However, it is hard to imagine that all these mechanisms are so strong to completely off-set the cumulative, dynamically increasing returns underlying the competitive advantages expected to characterize persistent innovators.

Our results speak more in favor of a second, alternative interpretation. They are in fact in agreement with theories of firm growth as well-described by an erratic pattern, essentially guided by luck (Barney, 1997). This view is supported by previous empirical studies that have questioned that the innovation-growth nexus is strong as often assumed (Coad, 2009; Audretsch et al., 2014). Our analysis adds to that literature, showing that not only innovation

[12] The Shorrocks index considers the degree of persistence on the main diagonal. In our case, working with quartiles, it has an upper bound of 4/3 for full mobility (i.e., no firms remain in initial quartile, thus all zeroes in the main diagonal) and a lower bound of 0 for maximal persistence (all ones in the main diagonal, as all firms remain in their initial quartile). The Bartholomew index, instead, also accounts for off-diagonal mobility, assigning higher weights to longer jumps. It takes value 0 for maximal persistence (all firms remain in their initial quartile), and goes to 1 for maximal mobility (all firms makes the longer possible jump compared to their initial quartile).

"per se", but also innovation persistence does not work as a robust predictor of subsequent sales expansion over the long run.

In terms of policy, it may be too early to provide definite conclusions, since our findings surely needs to be further corroborated on larger samples and in other countries. However, they cast doubts that policy makers could rely upon nurturing persistent innovators to promote long run growth of sectors and countries. Persistent innovators do exist, and some of them do exhibit outstanding performance. Yet, they are not generally able to grow more and more persistently than other firms.

Being to our knowledge the first study that directly tackles basic questions about the effect of innovation persistence on firms' sales growth, our work obviously represents an initial attempt along a much wider research agenda. Beyond expanding the analysis to other types of technological and non-technological innovations, two promising avenues of future research, in particular, could be developed within our framework, perhaps with more detailed data than we can access here. First, while we measure innovation persistence just in terms of frequency of innovation activities, it would be important to further characterize persistent innovators by the intensity and "quality" of their persistent innovative efforts. That is, to distinguish them, by the size of their repeated R&D investment, the number and type of product and process innovations introduced in consecutive years, or the quality and value of the patents that firms keeps to add to the already existing patent portfolios. This analysis would establish a connection to the literature on sources and persistence of technological leadership and the ensuing relations to industry dynamics (Fontana and Vezzulli, 2016). Second, it would be interesting to explore whether positive growth premia may eventually arise for firms jointly performing more than one technological activity persistently over time. That would complement recent research dealing with complementarities between technological activities in shaping sales growth trajectories (Bianchini et al., 2018b), adding to that literature a dimensions (innovation persistence) not yet considered.

More broadly, our negative results naturally lead to the question about which factors internal or external to the firm may lie behind firm growth patterns that are apparently driven exclusively by "mere luck". Deeper internal factors mostly relate to companies' managerial and organizational capabilities. These capabilities are often hardly measurable in standard available datasets, but they are are decisive for properly developing, designing and making innovations successful in economic terms. As for the external factors, the accumulation and diffusion of basic scientific knowledge, may turn crucial to intensify innovativeness at both the intensive and the extensive margin. This is particularly true if prevailing technologies: (i) entail a significant amount of preliminary research efforts to be developed; (ii) and/or are characterized by relevant uncertainty regarding their future development; (iii) and/or imply bearing an important sunk cost at the initial stages. On the other hand, the availability of an adequate supply (in terms of both quantity and quality) of managerial and worker-level skills is fundamental to allow the organizational upgrading needed to magnify the innovation-related economic benefits.

A deeper consideration of the interplay between our findings and these factors (and perhaps others, like obstacles to innovation) would also contribute to better inform and design policy intervention, against the otherwise little hope left from our results that supporting innovation persistence will "automatically" contribute to general economic growth. In fact, analysis of internal vs. external factors would allow to asses the relative merits of more micro policy measures (e.g., supporting education and training programs favoring technological upgrading of management and workforce) vis a vis more structural and systemic policies (e.g., funding public institutions producing basic research) in fostering growth and economic development possibly stemming from technological innovation persistence.

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Appendix A: Distributional analysis of growth and firm characteristics by persistence innovation status

We provide here a distributional comparison of the "identity cards" of persistent innovators vis a vis other firms, providing kernel estimates of the empirical distribution of growth and firm characteristics, pooling data over the period 2000-2012.[13]

In Figure 1 we plot (on a log-scale) the kernel densities of relative sales growth rates G. The estimates, in all groups, agree with the well known stylised fact that growth rates tend to display fat-tails and a tent-shaped behaviors. However, we do not observe striking difference across persistent innovators and other firms, independently from the innovation dimension involved. If anything, persistent innovators are less concentrated at the extremes of the support, in particular in upper tail in all densities, while also in the lower tail for persistent patenting firms. Yet, the shapes are quite similar across persistent innovators and other firms, and show a significant degree of overlapping in the portion of figures where most of probability mass lies. Low number of data point makes graphs at the extremes less reliable.

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 the firm size densities estimated for the other firms. Qualitatively similar results, though with

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

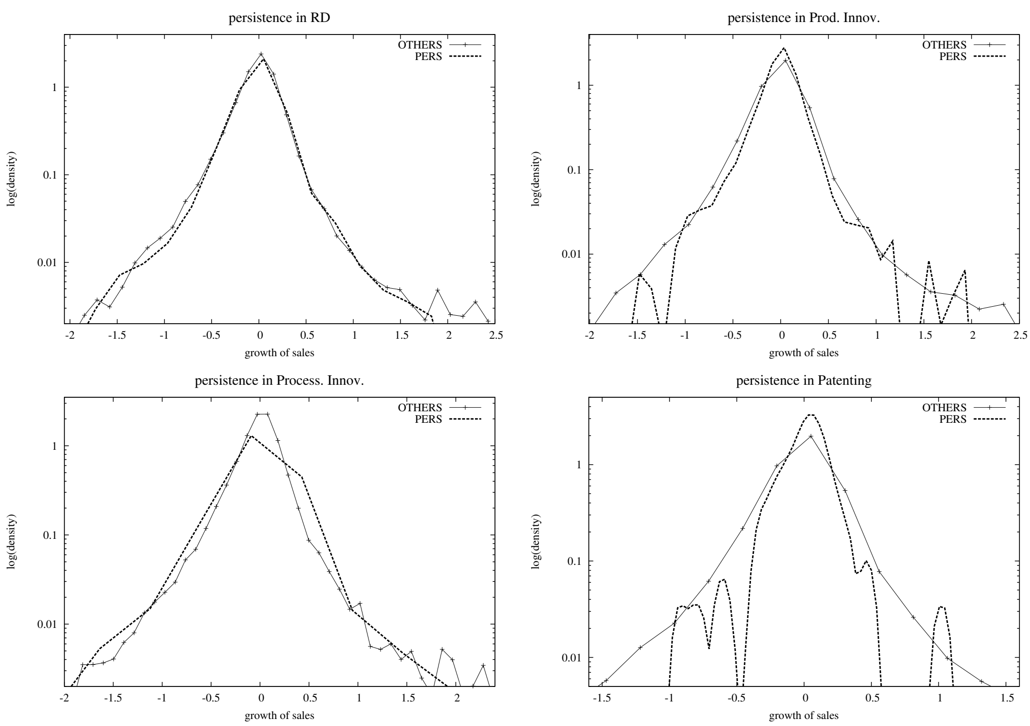

Figure 1: Kernel densities of sales growth G as defined in Eq. (1), for persistent innovators (PERS) vs. other firms (OTHERS), by different innovation persistence indicators.

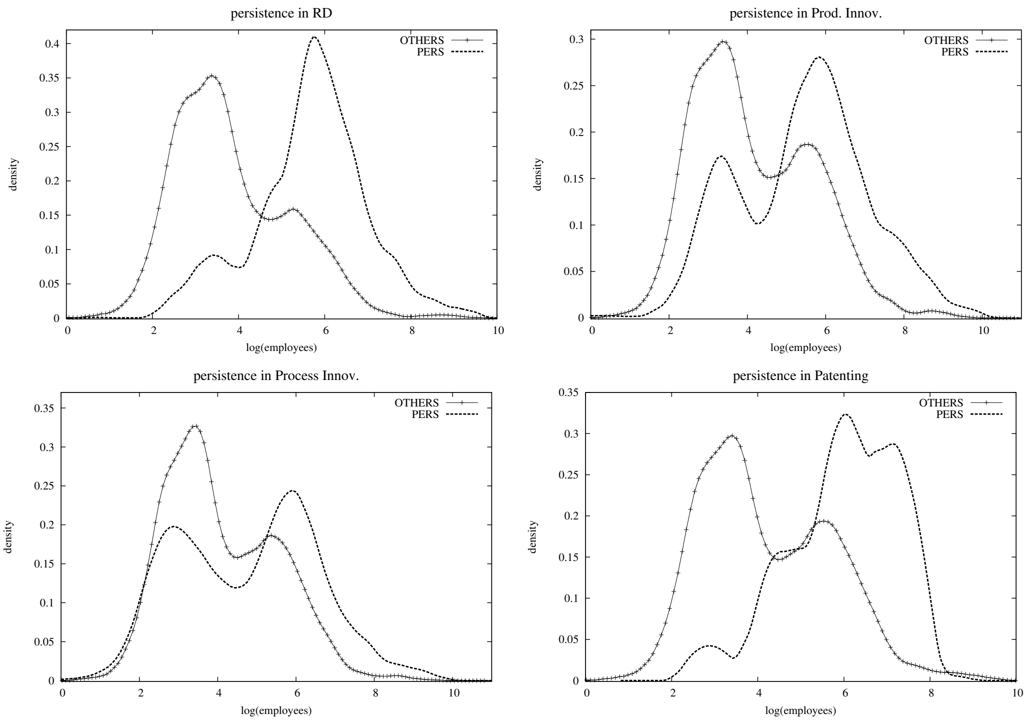

Figure 2: Kernel densities of firm size, as (log) employees, for persistent innovators (PERS) vs. other firms (OTHERS), by different innovation persistence indicators.

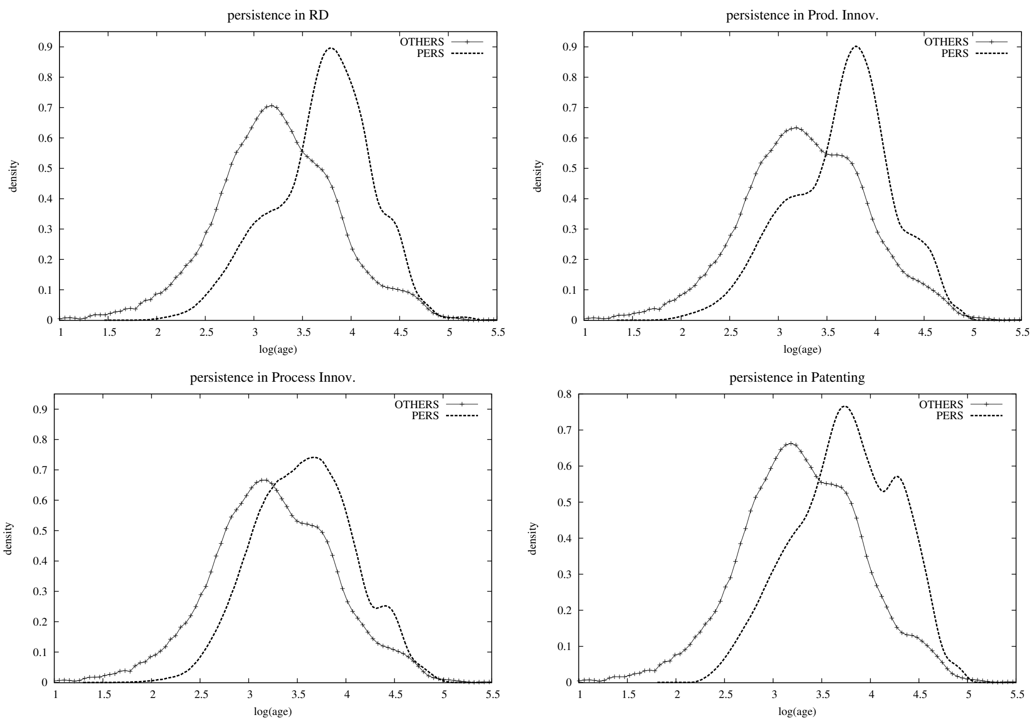

Figure 3: Kernel densities of (log) age, for persistent innovators (PERS) vs. other firms (OTHERS), by different innovation persistence indicators.

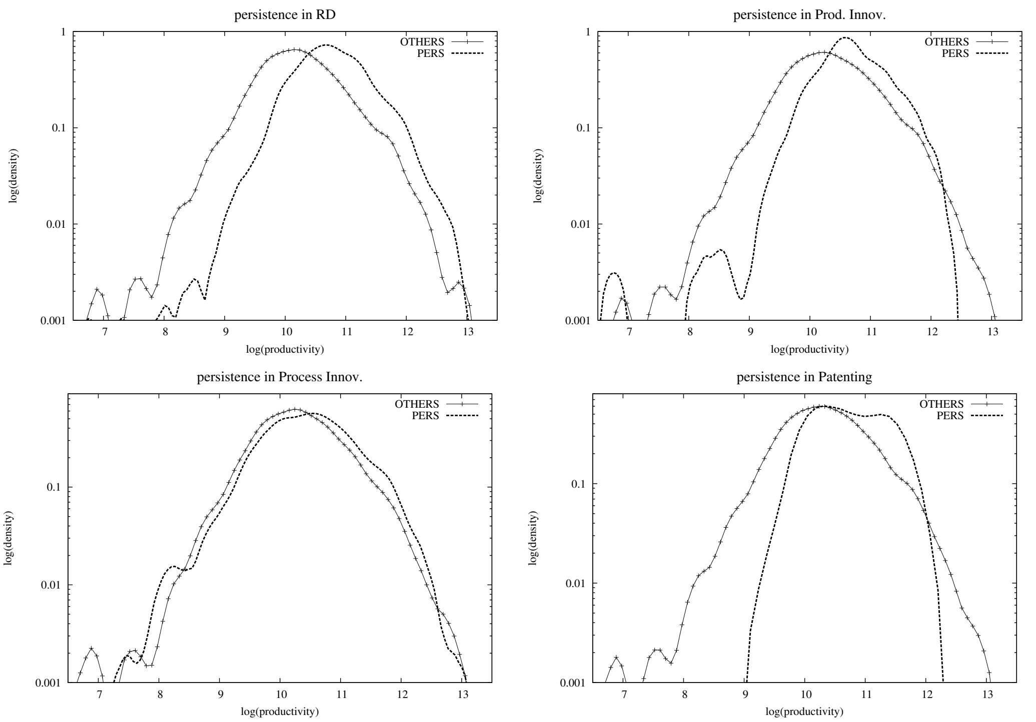

Figure 4: Kernel densities of (log) productivity as real value added per hour worked, for persistent innovators (PERS) vs. other firms (OTHERS), by different innovation persistence indicators.

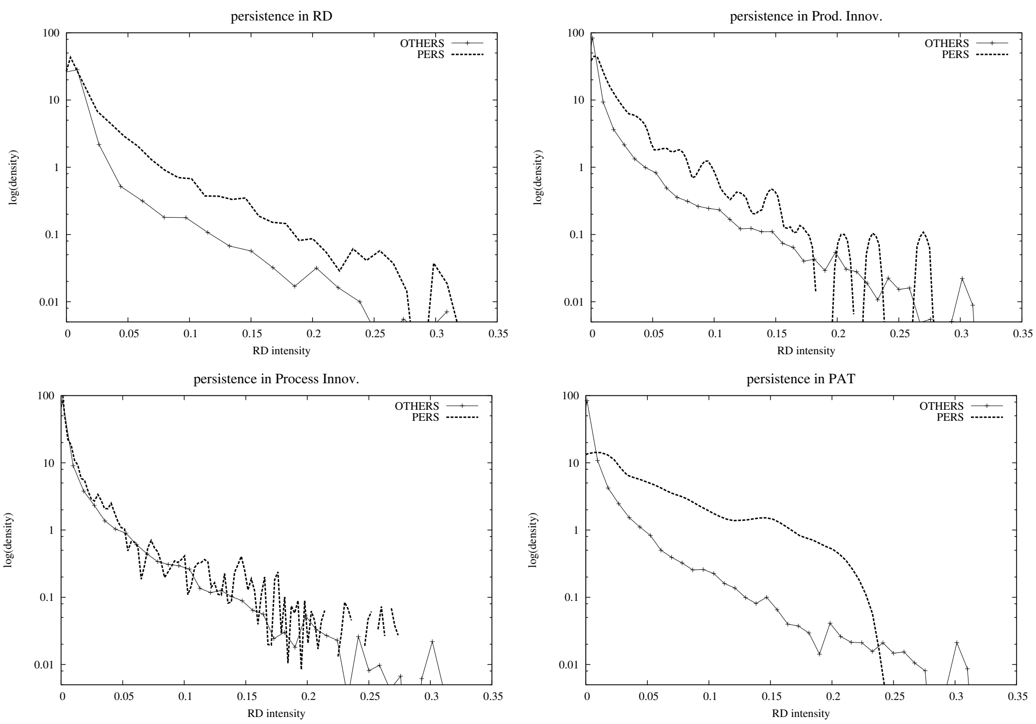

Figure 5: Kernel densities of R&D intensity, as the ratio of R&D expenses over sales, for persistent innovators (PERS) vs. other firms (OTHERS), by different innovation persistence indicators.

less marked bimodalities, emerge for firm age, in Figure 3. 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 distributions estimated for persistent innovators show more mass in the right half of the support, compared to the distributions estimated for other firms. Yet, persistent innovators seems less concentrated than other firms in the right and top quantiles (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.

Overall, we highlight two patterns. First, the analysis of unconditional empirical confirms the descriptive statistics reported in the text: persistent innovators do not seem to differ much from other firms in terms of growth, while they appear to be comparatively larger, older, and generally more productive and more intensive in R&D. But we can appreciate here that firms of different size, age, productivity ad R&D intensity are in fact present in all groups of both persistent innovators and other firms.

Second, distributional analysis adds to the well known stylised facts that growth rates are fat-tailed and firm characteristics highly skewed. We observe here, for the first time to our knowledge, that fat-tails, wide heterogeneity and skewness do replicate also within samples of persistent innovators, no matter the type of technological innovation in question.

Appendix B: Analysis of 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. In Table 11 we see that the pairwise correlations between controls are all relatively low, reassuring that the main estimates do not suffer from significant collinearity. In Table 12 we explore the relation between sales growth G and the controls (one by one and all together) in a set of basic OLS regressions excluding the main regressor PERS and the p-scores. Results replicate the patterns observed in the main analysis, reassuring that the controls are indeed good controls.

Table 11: Pairwise correlations

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

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

Table 12: Controls and firm growth, excluding PERS dummies

Dep. Variable is G_t	(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.

Table 13: Innovation persistence and firm growth, “6-out-of-10 years” PERS groups

	R&D PERS	PRODUCT PERS	PROCESS PERS	PATENT PERS
Pers dummy	-0.000893	0.00884	-0.00756	0.00276
	(0.00824)	(0.00923)	(0.00652)	(0.0154)
Age	0.00930	0.00909	0.0490**	0.000861
	(0.00801)	(0.00868)	(0.0161)	(0.00729)
Size (lag)	0.0324***	0.0342***	0.0377***	0.0249***
	(0.00550)	(0.00689)	(0.00593)	(0.00499)
Productivity (lag)	-0.0424***	-0.0476***	-0.0526***	-0.0421***
	(0.00924)	(0.0103)	(0.0105)	(0.00959)
R&D intensity (lag)	0.996***	1.029***	0.866***	0.961***
	(0.207)	(0.225)	(0.180)	(0.238)
P-score	-0.136**	-0.499*	-0.480***	-0.529
	(0.0447)	(0.196)	(0.122)	(0.360)
Constant	0.235**	0.290**	0.263**	0.278**
	(0.0858)	(0.0889)	(0.0854)	(0.0882)
Observations	10450	10450	10450	10450

Notes: Estimates of growth-premium. All specifications also include year and sector fixed effects. Bootstrap standard errors (100 replications) in parenthesis below the coefficients. Asterisks denote significance levels: * p<0.05, ** p<0.01, *** p<0.001.

Appendix C: Robustness checks

As mentioned in the main text, the baseline estimates presented in Section 4 were tested against a series of robustness checks. We discuss them in this Appendix.[14]

First, we experimented with a less conservative definition of persistent innovators, taking as PERS= 1 the firms innovating consecutively for at least 6 years over the period 1990-99, instead of the “7-out-of-10 consecutive years” criterion used in our main analysis. This essentially allows for some more “infrequent” or “occasional” innovator to enter the groups. Then, we re-estimated our baseline regressions in Equations (3) and (4) including this different definition of PERS dummies. The results (in Table 13 and Table 14) confirm our baseline conclusions.[15]

Next, we present two exercises that allow us to exploit the panel structure of the data, in turn applying GMM-panel techniques to control for firm fixed-effect, and endogeneity of both innovation persistence dummies and control variables. Panel techniques cannot be applied in our baseline framework, since the PERS dummies do not vary over the regression period 2000-2012.

[14]We also performed two additional unreported robustness checks. First, 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. Second, we also experimented with including in Equation (3) and Equation (4) p-scores obtained via an alternative first-step Probit where persistent innovator status is regressed against the covariates measured over the estimation time-period 2000-2012. In all these additional analysis, our main conclusions still apply. The results are available upon request.

[15]Each specification implies to re-define PERS groups and, thus, the p-scores entering the estimates.

Table 14: Innovation persistence and persistence of growth, "6-out-of-10 years" PERS groups

	R&D PERS	PRODUCT PERS	PROCESS PERS	PATENT PERS
Pers dummy	-0.00110	0.00646	-0.00305	0.00986
	(0.00894)	(0.00982)	(0.00720)	(0.0173)
Sales growth (lag)	-0.0262	-0.0428	-0.0265	-0.0367
	(0.0215)	(0.0233)	(0.0214)	(0.0227)
Interaction	-0.0487	0.0754	-0.0326	-0.00143
	(0.0563)	(0.0532)	(0.0531)	(0.0909)
Age	0.00987	0.0103	0.0526**	0.000591
	(0.00911)	(0.00981)	(0.0182)	(0.00827)
Size (lag)	0.0347***	0.0373***	0.0394***	0.0270***
	(0.00597)	(0.00742)	(0.00639)	(0.00534)
Productivity (lag)	-0.0394***	-0.0455***	-0.0506***	-0.0398***
	(0.00912)	(0.0105)	(0.0108)	(0.00972)
R&D intensity (lag)	1.016***	1.073***	0.860***	1.000***
	(0.215)	(0.237)	(0.184)	(0.251)
P-score	-0.152**	-0.577**	-0.513***	-0.658
	(0.0497)	(0.214)	(0.134)	(0.392)
Constant	0.287***	0.346***	0.322***	0.339***
	(0.0855)	(0.0889)	(0.0865)	(0.0887)
Observations	9158	9158	9158	9158

Notes: Estimates of growth-persistence premium. All specifications also include year and sector fixed effects. Bootstrap standard errors (100 replications) in parenthesis below the coefficients. Asterisks denote significance levels: * p<0.05, ** p<0.01, *** p<0.001.

A first robustness exercise concerns the investigation of Hypothesis 1on growth-premia. We change the definition of PERS groups in such a way to allow PERS status to vary over time. We define as PERS= 1 a firm that has performed a given innovation activity *consecutively in the previous 7 years*. The first 7 years of data are lost, but we can exploit the time span 1997-2012 to run the following modified specification of Equation (3)

$$G_{it} = \beta_0 + \beta_1\ PERS_{it} + \beta_2\ X_{it-1} + u_{it} \quad . \tag{5}$$

where now each firm can in principle become (or cease to be) PERS over the period. Compared to our baseline empirical strategy, this alternative framework shifts the focus from the "longer-run" perspective we are originally interested into, to a shorter-run (contemporaneous) analysis of the relation linking growth and innovation persistence. Also, the classification into the four PERS groups is more prone to be endogenous. Nonetheless, panel-GMM techniques can be applied to exactly address this issue, in turn avoiding to resort to Probit p-score corrections.

Table 15 reports the results obtained via GMM-DIFF estimator.[16] The results essentially

[16]This is more appropriate than the alternative GMM-SYS estimator, given the relatively low degree of persistence of our dependent variable. In fact, GMM-SYS performs 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

Table 15: Innovation persistence and firm growth with time-varying PERS dummies

	R&D PERS	PROCESS PERS	PRODUCT PERS	PATENT PERS
Pers dummy	0.0698	0.0515	0.146	0.0319
	(0.0560)	(0.0367)	(0.101)	(0.148)
Age	-0.171*	-0.0809	-0.0860	-0.189*
	(0.0828)	(0.0641)	(0.0645)	(0.0781)
Size (lag)	0.116	-0.0449	-0.0292	0.120
	(0.221)	(0.170)	(0.146)	(0.280)
Productivity (lag)	-0.371*	-0.284*	-0.280*	0.0288
	(0.179)	(0.115)	(0.117)	(0.137)
R&D intensity (lag)	-2.394	-0.277	-0.374	-0.123
	(1.588)	(1.386)	(1.168)	(2.621)
Observations	14484	14484	14484	13094
IV diagnostics: stat (p-value)				
AR(1) residuals:	-7.76(0.000)	-8.32(0.000)	-8.79(0.000)	-6.77(0.000)
AR(2) residuals:	-1.48(0.141)	-1.42(0.155)	-1.45(0.148)	-1.29(0.197)
Hansen test:	70.70(0.122)	164.97(0.123)	182.02(0.146)	29.84(0.190)

Notes: GMM-DIFF two-step estimates of growth-premium for persistent innovators, defined as firms performing a given innovation activity consecutively in the previous 7-years. All specifications also include year and sector fixed effects. Robust standard errors in parenthesis, with Windmeijer (2005) small sample correction. Asterisks denote significance levels: * p<0.05, ** p<0.01, *** p<0.001.

confirm our main conclusion: persistent innovators do not enjoy a statistically significant growth-premium, no matter the innovation dimension considered.

We further exploit the panel structure of the data to also test Hypothesis 2 about growth-persistence premia. We keep our baseline framework with time-invariant PERS groups defined over the period 1990-1999, but we exploit the time dimension over the period 2000-2012 by running a split-sample analysis of sales growth autocorrelation, separately by persistent innovators and other firms. In practice, we estimate the following variation of the baseline Equation (4)

$$G_{it} = \gamma_0 + \gamma_1\, G_{it-1} + \gamma_2\, X_{it-1} + u_{it}\ , \tag{6}$$

separately for persistent innovators (PERS= 1) and other firms (PERS= 0), as identified according to the different innovation indicators. All the regressors are time-varying, and we can again apply panel methods to control for endogeneity of both lagged growth and covariates. Evidence of a "growth persistence premium" is revealed by comparing the estimated γ_1 across persistent innovators and other firms.

Table 16 reports the findings obtained via a GMM-DIFF estimator.[17] We once again confirm our main conclusion that growth patterns of persistent innovators do not display more persistence compared to other firms. The estimated γ_1 are not statistically significant, neither for PERS=1 nor for PERS=0 in the models where when we split firms according to persis-

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.

[17] Also in this case we use a two-step GMM-DIFF estimator, with the Windmeijer (2005) small sample correction of the standard errors and taking as instruments various lags of growth, size, productivity and R&D, while age, sector fixed-effects and year fixed-effects are assumed exogenous.

Table 16: 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 (6), across persistent innovators (PERS= 1) and other firms (PERS= 0) as identified by different innovation persistence indicators. All specifications also include year and sector fixed effects. Robust standard errors in parenthesis, with Windmeijer (2005) small sample correction. Asterisks denote significance levels: * p<0.05, ** p<0.01, *** p<0.001.

tence in R&D, product innovation and patenting. The split-sample estimates based on process innovation persistence show negative autocorrelation within both persistent innovators and other firms, but there is no statistical difference between the two groups: point estimates of γ_1 completely overlap within a 1-standard error confidence band.

Appendix D: Additional extended analysis

We also document about two additional exercises performed to further corroborate the extended analysis of Section 5.

First, as a further investigation that firm size is not driving our main findings, due to persistent innovators being comparatively larger than other firms, we re-estimate the baseline specifications in Equations (3) and (4), now including size-squared as additional regressor. Results in Table 17 and Table 18 are once again in line with baseline findings.

Next, in Table 19 we show 5-years transition probabilities across quartiles of yearly sales growth distributions. Results are in line with the 3-years transitions reported in the main text, confirming that persistent innovators do not exhibit differences in growth persistence as compared to other firms.

Table 17: Growth premium - Adding size squared

	(1) R&D	(2) PROC	(3) PROD	(4) PAT
PERS dummy	-0.00903	-0.00800	0.0127	-0.00272
	(0.00739)	(0.00708)	(0.00894)	(0.0146)
Age	0.00511	0.0188	0.00956	0.0557*
	(0.00710)	(0.0130)	(0.0117)	(0.0250)
Size	0.0334**	0.0327**	0.0145	0.0330**
	(0.0107)	(0.0104)	(0.0160)	(0.0107)
Productivity	-0.0379***	-0.0456***	-0.0476***	-0.0540***
	(0.00740)	(0.00991)	(0.0117)	(0.0123)
R&D Intensity	1.116***	1.099***	1.072***	1.003***
	(0.212)	(0.239)	(0.231)	(0.203)
Size^2	0.000536	0.00170	0.00398	-0.00115
	(0.00149)	(0.00170)	(0.00335)	(0.00110)
P-score	-0.183*	-0.447*	-0.697*	-0.998**
	(0.0788)	(0.189)	(0.353)	(0.386)
Constant	0.166*	0.224**	0.287**	0.241**
	(0.0742)	(0.0817)	(0.107)	(0.0922)
Observations	11693	11693	11681	11693

Notes: OLS estimates. All specifications also include year and sector fixed effects. Bootstrap standard errors (100 replications) in parenthesis below the coefficients. Asterisks denote significance levels: * p<0.05, ** p<0.01, *** p<0.001.

Table 18: Growth persistence premium - Adding size squared

	(1) R&D	(2) PROC	(3) PROD	(4) PAT
PERS dummy	-0.00817	-0.00506	0.0137	0.000747
	(0.00928)	(0.00822)	(0.0107)	(0.0155)
Sales Growth (lag)	-0.0195	-0.0187	-0.0303	-0.0215
	(0.0189)	(0.0178)	(0.0219)	(0.0223)
Interaction	-0.0516	-0.0437	0.0218	-0.0726
	(0.0626)	(0.0570)	(0.0683)	(0.133)
Age	0.00905	0.0255	0.0136	0.0644
	(0.00845)	(0.0154)	(0.0128)	(0.0340)
Size	0.0361***	0.0372**	0.0138	0.0367**
	(0.0107)	(0.0114)	(0.0151)	(0.0113)
Productivity	-0.0376***	-0.0468***	-0.0488***	-0.0545***
	(0.00889)	(0.0115)	(0.0131)	(0.0155)
R&D Intensity	1.215***	1.165***	1.129***	1.012***
	(0.249)	(0.242)	(0.233)	(0.211)
Size^2	0.00113	0.00216	0.00504	-0.00142
	(0.00169)	(0.00214)	(0.00341)	(0.00128)
P-score	-0.253**	-0.566*	-0.871*	-1.104*
	(0.0889)	(0.222)	(0.390)	(0.491)
Constant	0.148	0.215*	0.290*	0.222*
	(0.0794)	(0.0873)	(0.115)	(0.102)
Observations	10246	10246	10246	10246

Notes: OLS estimates. All specifications also include year and sector fixed effects. Bootstrap standard errors (100 replications) in parenthesis below the coefficients. Asterisks denote significance levels: * p<0.05, ** p<0.01, *** p<0.001.

Table 19: Growth persistence premium, 5-years transitions across growth quartiles

			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	*t*	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	*t*	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	*t*	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	*t*	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.