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Innovation Strategies and Firm Growth

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Innovation Strategies and Firm Growth*

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Abstract

In this work, we explore the relations between sales growth and a set of innovation indicators that capture the different sources, modes and results of the innovative activity undertaken within firms. We exploit a rich panel on innovation activity of Spanish manufacturing firms, reporting detailed CIS-type information continuously over the period 2004-2011. Standard GMM-panel estimates of the average effect of innovation activities reveal significant and positive effect for internal R&D, while no effect is found for external sourcing of knowledge (external R&D, acquisition of embodied and disembodied technologies) as well as for output of innovation (process and product innovation). However, fixed-effects quantile regressions reveal that innovation activities, apart from process innovation and disembodied technical change, display a positive effect on high-growth performance. Finally, we find evidence of super-modularity of the growth function, revealing complementarities of internal R&D with product innovation, and between product and process innovation.

JEL codes: C21, D22, O31, O32

Keywords: firm growth, product and process innovation, internal and external R&D, embodied and disembodied technical change, fixed-effects quantile regressions, complementarity

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1 Introduction

The relation between innovation and firm growth is a classical, yet still puzzling topic. The general intuition is obviously that innovation is among the key determinants of comparative advantages over competitors, thus contributing to the ability of firms to grow and gain market shares. Against this simplistic prediction, however, play the ample degrees of complexity, uncertainty and idiosyncrasy that are well known to characterize the innovation process. Innovation is the search for, and the discovery, development, improvement, adoption and commercialization of, new processes, new products and new organizational structures and procedures. It involves indeed uncertainty, risk taking, probing and re-probing, experimenting and testing. Thus the process of innovation itself, and its ensuing effects on various aspects of firm performance, can be extremely heterogeneous and difficult to predict.

Within the vast literature, this paper contributes to the studies that seek to identify the links between innovation and success on the market in terms of sales growth. In spite of the increasing availability of firm level data over the last 10-15 years, especially following the attempt undertaken by the EU to provide regular surveys of innovation across members states (the CIS-*Community Innovation Survey* exercise), this literature is still underdeveloped under several respects, in turn motivating the contributions that we want to pursue in this study.

First, our major contribution is to provide a broad picture of the relation between growth and innovation, by looking at a wide set of innovation indicators that capture different sources, modes and output of the innovative efforts undertaken by firms. Indeed, while extant empirical studies on growth and innovation mostly focus on traditional proxies such as R&D and patents, the multifaceted nature of innovation as well as the great variety of innovation strategies undertaken by firms calls for a multi-dimensional approach to assess the actual contribution of innovation on corporate growth (Audretsch et al., 2014). Exploiting a rich dataset on Spanish firms, we can use a set of innovation indicators including internal vs. external R&D, process vs. product innovation, also distinguishing between products new-to-the-firm vs. new-to-the-market, investment in innovative machineries, and purchase of licenses or know-how from other firms. This allows us cover the usual dichotomy between innovative inputs vs. innovative outputs, but also to investigate the role of internal vs. external sourcing of knowledge. The existing literature does not provide conclusive evidence on their relation with sales growth. In this respect our paper is closely related to the recent work by Hölzl (2009) focusing on high-growth firms. The cross-sectional nature of that study, however, represents a limitation we want to improve upon.

Indeed, our second contribution stems from the possibility to work with a panel of firms observed over several years. A common limitation to studies exploiting CIS-like data is that such surveys are run in waves every 3-4 years, often on rotating samples of firms. Thus, previous studies can typically exploit a single cross section, or they can follow just a few firms over time, in turn failing to control for unobserved heterogeneity. This point is not merely a technical econometric drawback, given the inherently idiosyncratic nature of the process and outcomes of innovation. The dataset of Spanish firms available to us is a CIS-type dataset in terms of the rich and detailed information about innovative activity, but it is longitudinal in nature, since a consistent data collection methodology ensures to have information on the same set of firms over time.

Third, and relatedly, we also contribute to the recent literature (Coad and Rao, 2008; Falk, 2012; Segarra and Teruel, 2014) that adopts quantile regressions to show that while innovation can have mixed or nil effect on the average growth rate in a cross section of firms, innovation is indeed more beneficial for fast-growing, firms. Besides mostly focusing only on patents or R&D, these studies apply basic quantile regression techniques, with few exceptions (Coad et al., 2016; Mazzucato and Parris, 2015). Exploiting the longitudinal dimension of our data, we can instead apply up-to-date quantile regression techniques designed to account for firm fixed effects.

Finally, we provide an empirical assessment of the complementarities existing between the different innovation activities in favoring sales growth. Recent studies exploit the notion of modularity of the innovation function to investigate the complementarity of innovation inputs or knowledge sources in successful generation of innovation output. We apply the same conceptual and statistical framework to ask whether different combinations of basic innovation activities (internal and external R&D, process and product innovation, embodied and disembodied technical change) help improving growth performance, above and beyond the contribution of each single activity alone.

Our results point to a good deal of heterogeneity in the way different innovation activities contribute to expanding sales. Indeed, among the innovation indicators we account for, internal R&D turns out as the main driver of sales growth, on average. Other innovation activities, with exception of disembodied technical change and process innovation, have a positive association with growth only for high-growth firms in the top quantiles of the firms' growth rates distribution. We also document a complementarity effect between internal R&D and product innovation, and between product and process innovation. This evidence emphasizes the complexity underlying the growth-innovation relation and provides a potential explanation for the inconclusive results of previous studies which adopted a unidimensional approach.

2 Background literature and research questions

The starting point of our analysis rests in the failure of the existing literature to provide a comprehensive account of the multifaceted nature of the innovation process. As Audretsch et al. (2014) put it in an up-to-date review of the literature "...the complexity of R&D activities, together with the diversity of innovation strategies and the multiplicity of growth modes, requires a multidimensional approach to examine the contribution of innovations on firm growth." Indeed, different innovation activities are usually undertaken and combined within the innovative efforts of heterogeneous firms, with differentiated impact on their ability to sustain competition and ultimately gain or loose market shares.

Whilst theoretical models from different traditions acknowledge the importance of innovation as a major driver of firm growth and success on the market (from the Schumpeterian-evolutionary tradition related to Nelson and Winter (1982), to new-growth theories and more recent neo-classical or neo-Schumpeterian models as in Aghion and Howitt (1992) and Aghion et al. (2005), among others), the empirical literature does not fully support the theoretical expectations. This is in particular the case when one looks at the effect of innovation on the growth rate of the "average firm", through standard regression estimates, while some more recent analyses partly reconcile theory and evidence showing that innovation tends indeed to support the growth of high-growth firms.

In this Section we discuss the reference literature on the relations between innovation activities and firm growth, as a background that motivates the research hypotheses that we tackle in this paper.

We refer to studies investigating sales growth, which are more directly related to our analysis.[1]

2.1 Innovative inputs, innovative outputs and their relation with average growth

Empirical studies traditionally apply standard regression techniques to estimate the impact of innovation on average sales growth. Internal R&D and patents represent the two traditional proxies of innovative activities, respectively capturing the input and the output side of the innovation process. A fair reading of a vast literature, impossible to summarise here, is that it has been difficult to find a strong support for a positive effect of innovation on sales growth. The early papers did document a positive effect, especially for R&D (Mansfield, 1962; Mowery, 1983), and many subsequent papers corroborates that innovating firms grow faster, highlighting the sometimes transitory nature of success in the market(Geroski and Machin, 1992), the role of size and age (with smaller and younger innovators achieving a more rapid growth, see e.g. Storey, 1994), and the differentiated results across low vs. high tech sectors (Stam and Wennberg, 2009). By contrast, however, a large number of studies do not find any significant effect of R&D or patenting activity on sales growth (see, among the many, Geroski et al., 1997; Geroski and Mazzucato, 2002; Bottazzi et al., 2001), also in this case highlighting the interplay of innovation with size, age and other firm or sectoral characteristics (see Audretsch et al., 2014, for a review).

While this lack of a robust relation echoes the more general issue about the unpredictability of growth (Geroski, 2002), the complexity and the uncertain nature of the firms' innovative process as well as criticisms to the adopted proxies of innovation, have been advanced as specific explanations, in turn motivating efforts to measure innovation more accurately. A more recent literature therefore takes advantage of more detailed data that allow to take into account different proxies of both inputs and outputs of innovation, drawing especially from surveys like the European CIS and similar data around the world.

Concerning the output side of innovation, many studies highlight the merits of innovation surveys in providing direct proxies for product and process innovations (see Griffith et al. 2006; Parisi et al. 2006; Hall et al. 2008, 2009), beyond traditional focus on patents. However, as a matter of fact, only few works consider the relation between sales growth and proxies of innovative output alternative to patents.

On the one hand, there is practically no evidence about the direct impact of process innovation on sales growth, as indeed most studies focus on the relation between new processes and productivity (see Griffith et al. 2006; Hall et al. 2009; Mairesse and Robin 2009). A notable exception is in Goedhuys and Veugelers (2012), who find that process innovation has no effect on sales growth on a sample of Brazilian manufacturing firms. The interpretation is that of a mediating role of productivity, such that process innovation has direct effect on cost efficient production, while it may show its beneficial effects on sales in later stages, after an initial period of process restructuring.

On the other hand, concerning product innovation, theory would predict a positive link between the introduction of new products and sales growth, as indeed efforts directed to creation and commercialization of new products represent the primer strategy for expansion and growth (Hay and

[1] There also exists a huge literature on the effects of different types of innovation on growth of employment, where the main focus is on the lost-lasting debate on the labour-saving vs. labour augmenting effect of innovation (see Vivarelli, 2014, for an exhaustive survey). We do not discuss this literature here, as we are more interested in a measure of growth capturing success on the market.

Kamshad, 1994). But the evidence is mixed. For instance, Cucculelli and Ermini (2012) find that product innovation (measured as a dummy for introduction of new products) does not affect sales growth, and one has to control for the tenure from last product introduction to recover some positive effect. Other studies suggest that product characteristics matter beyond the mere ability to introduce new products in the market. In this respect, the literature focuses on two measures of product innovation that we also use, that is distinguishing between products-new-to-the-firm vs. products-new-to-the market, again with mixed results. The cross-country evidence in Hölzl (2009) lends support to the intuition that products-new-to-the-market, capturing more original and potentially more disruptive innovation are those that really matters for competing and gaining market shares, as compared to more imitative efforts related to products new-only-to-the-firm. Conversely, however, Corsino and Gabriele (2011) find on Italian data that sales growth is positively affected also by more incremental product innovations introduced in the recent past, even if the latter are related to less valuable innovations or to imitative efforts. The specificity of the country may play a role, of course, allowing even less valuable innovation to support market shares.

Moving to the relation between sales growth and innovation inputs, the literature has been sort of resilient to in-house formal R&D. Innovation surveys, much like indeed our dataset, provide rich information also about external sourcing of knowledge, such as purchases of external R&D and acquisition of innovative technology, both embodied (investment in innovative machinery and equipment) and disembodied (acquisition of patents, know-how, licenses). Theoretically, the acquisition of new knowledge or new techniques from outside the boundaries of the firm has uncertain effects. On the one hand, external sourcing can help improving the knowledge base and, thus, the overall innovative capabilities of firms. And this can be sometimes the only viable strategy to pursue, especially for smaller or more traditional firms that do not have internal capabilities to support formalized internal research. On the other hand, however, the actual exploitation of external sourcing can be hampered by lacking absorptive capacities, by complexity and coordination issues arising within the user-producer interactions, and by the non-trivial challenges related to the adaptation of the outsourced innovative inputs to the specific characteristics, competences and needs of each firm. And the overall effect on growth also depends from the type of outsourced knowledge, as a key decision is about externalizing "core activities", more likely to be related to new products' development and growth, vs. more "marginal activities", that are less likely to impact on sales and market shares.

The evidence from innovation studies supports a positive impact of external innovation on both product and process innovation (Santamaria et al., 2009; Pellegrino et al., 2012; Goedhuys and Veugelers, 2012; Conte and Vivarelli, 2014). However, we lack systematic evidence about the effect of external sourcing of knowledge and innovation on sales growth. An exception is in Segarra and Teruel (2014), who document that external R&D has a significantly smaller impact than in-house R&D.

Overall, from a joint reading of the literature, we can sketch a set of predictions concerning the effect on *average* sales growth of the different proxies of innovative activity considered in this work.

First, we expect internal R&D to be positively associated with sales growth, although the uncertainty and complexity of the processes leading from search to actual market exploitation of innovation is likely to entail heterogenous effects across different firms.

Second, concerning the direct measures of product innovation, we expect in general that the ability of introducing new products should favor sales growth, although products new-to-the-firm and products new-to-the-market, respectively capturing more incremental vs. more substantial innovations, can be more or less beneficial depending on the sector and market characteristics.

Third, we can predict a relatively minor role of process innovation, whose effect on sales is mediated by the relevance of cost and efficiency factors as drivers of competition for market shares.

Fourth, concerning measures of external inputs of new knowledge and innovation, a number of theoretical reasons undermine the potential of these activities in fostering sales growth. We expect sales growth to more likely benefit from purchases of external R&D insofar as the latter is more directly linked to core activities, for which absorptive capacity and user-producer interactions should be less critical. Acquisitions of embodied technology (innovative machineries) are expected to support sales growth in so far as they are generally undertaken as a way to improve quality of products and processes. But also in this case there might be issues about a smooth incorporation of innovative capital within the firm. Similarly, the extent to which acquisitions of disembodied technology can contribute to sales growth largely depends from whether the firm enjoys the required capabilities to master and exploit the acquired stock of external knowledge.

Some of these hypotheses have received attention in previous studies in different datasets covering different countries and time periods. A key contribution will hopefully come from investigating all of them jointly on the same dataset.

2.2 Asymmetric effects of innovation across growth quantiles

One of the major robust stylised fact emerging from industrial economics is that the firm growth rates distribution is characterised by wide heterogeneity and a tent shape, whatever the level of sectoral aggregation considered (Stanley et al., 1996; Bottazzi and Secchi, 2006; Coad, 2009; Dosi, 2007). In this respect, due to its inherent nature, the processes leading from innovative input to innovative output may show different effects according to the different positioning of a firm in the growth rates distribution, beyond the effect on growth of the "average firm".

Motivated by these considerations, a recent literature applies quantile regression techniques to disentangle the effect of innovation proxies along the spectrum of the distribution of growth rates (Freel, 2000; Coad and Rao, 2008; Hölzl, 2009; Falk, 2012; Nunes et al., 2012; Colombelli et al., 2013). The general conclusion is that innovation, proxied by different innovation measures, is positively related with sales growth of high growth firms in the top quantiles of the growth rates distribution (see Coad et al., 2014, for a recent review).

While quantile regressions has allowed to, at least partially, reconcile the evidence with the theoretical expectation of a positive influence of innovation on firm growth, the literature still suffers from several limitations. First, most studies use R&D and patents as the only proxy of innovation, and there are only few attempts to expand along different innovation activities. The above-mentioned Segarra and Teruel (2014) show that external R&D does not matter for high-growth, while Hölzl (2009) exploit several measures much in the same line as we do here, although within a single cross-section. Second, existing evidence mostly originates from standard quantile regression methods, which do not control for unobserved idiosyncratic factors. Notable exceptions are in Coad et al. (2016) and Mazzucato and Parris (2015), who apply the same Canay (2011) fixed-effects quantile regression method that we exploit in this study, although taking traditional proxies of innovation.

Overall, we lack a solid guidance from theory and previous analysis about the relevance for fast vs. slow growing firms of all the different innovation dimensions considered in this study. At a general level, all the theoretical considerations pertaining to the effect of innovation activities on average growth remain valid also when considering the effect along the growth distribution quantiles. Our main working hypothesis is that high-growth firms should benefit more from innovation, no matter the innovation proxy considered, as compared to slow-growing or shrinking firms. Indeed, high-growth firms are expected to be more capable to deliver new and more valuable products, to better manage process innovation, and to more effectively solve the challenges related to external sourcing of new knowledge and technical change. We thus foresee a stronger and generally positive relation between sales growth and innovation variables in the top quantiles of the growth rates distribution.

2.3 Innovation complementarities and firm growth

Beyond investigating whether different innovation activities correlate with sales growth, a natural step forward is to ask whether it is the combination of different innovative activities, rather than each single activity per se, that matters for sales growth. In reality, indeed, firms can differently combine different inputs and outputs (Karlsson and Tavassoli, 2016). The effect that innovation has on sales growth can be different depending on the complexity of the strategy pursued, in terms of the number and the type of innovation activities performed at the same time. Each different combination may entail specific costs and challenging coordination issues, while also increasing the ability to create and capture growth opportunities.

An established empirical framework to reconstruct the interactions among different innovation activities and the ensuing impact on firm performance is via the CDM model (Crepon et al., 1998). Within a huge literature, studies mostly focus on the sources of productivity growth, and most often consider only one input (R&D in particular) and one output of innovation (see Mairesse and Mohnen, 2010, for a review). To our knowledge, the already mentioned Goedhuys and Veugelers (2012) represents the only attempt to assess the relevance of internal vs. external inputs for the generation of product and process innovation, and then to estimate the ensuing impact of successful new processes or products on stimulating sales growth.

We provide a different contribution by exploring the pairwise complementarities between internal R&D, product innovation, process innovation and external sourcing of knowledge. Among the different empirical methods to assess complementarities (Topkis, 1998), we exploit the notion of super-modularity, following a well established tradition in innovation studies that look at whether different innovation inputs or obstacles to innovation are complements in the generation of innovation output (Leiponen, 2005; Mohnen and Roller, 2005; Cassiman and Veugelers, 2006; Catozzella and Vivarelli, 2014). We apply the same framework to assess complementarities of innovation activities in the sales growth function.

Since this is the first attempt along this direction it is thus difficult to provide sharp predictions. From the above discussion on the potential benefits and constraints characterizing the innovation-growth relations along the different proxies of innovation, we outline the following working hypotheses. First, to the extent that R&D captures the internal stock of knowledge and overall firms' efforts to build innovative capabilities, we expect R&D to display complementarities with all the other innovation activities in sustaining sales growth. Indeed, on the output side, R&D is likely to ease the introduction and the quality of new products, and to improve the ability to master new processes. On the input side, R&D should help building the absorptive capacity required to tackle the challenges from external sourcing of knowledge.

Second, and relatedly, we expect external sourcing of innovation to have uncertain complementarity with both product and process innovation. Indeed, whether the additional complexity and challenges related to managing external sources of new knowledge are smoothly combined with new products and processes is not trivial a priori.

Third, we do not expect process innovation to exhibit, in general, any strong complementarity with other innovation variables, since its primer impact is typically on efficiency, and only indirectly on growth. However, a virtuous combination of new processes and new products can provide a sound mix of cost and product competitive advantages that may eventually results into increased ability to compete on sales. Thus, if process innovation has any effect, then we expect process innovation to be complement to product innovation.

Our results will hopefully provide new evidence to inform subsequent theoretical developments which rest outside the aims of this article.

3 The data

In this Section we present the sample and the main variables that we use in the empirical analysis.

3.1 Data and sample

We exploit a firm-level dataset drawn from the Spanish Technological Innovation Panel (henceforth PITEC), jointly developed by the Spanish National Statistic Institute (INE), the Spanish Foundation for Science and Technology (FECYT), and the Foundation for Technical Innovation (COTEC). The data are collected following the Oslo Manual guidelines (OECD, 1997) and, as such, they can be considered a Community Innovation Survey (CIS)-type dataset. Thus, PITEC includes a rich set of variables that measure firms' engagement in innovation activity, economic and non-economic measures of the effects of innovation, self-reported evaluations of factors hampering or fostering innovation, participation in cooperative innovation activities, access to public funding, use of patents and other means of appropriability, and some complementary innovation activities such as organizational innovation and marketing. The main limitation, common to other CIS-type surveys, lies in the relatively limited information about more structural and industrial characteristics of firms, which essentially cover only annual sales and employment, industry affiliation, founding year, export status, industrial group, and few others.

The key feature that distinguishes PITEC from the majority of European CIS-type datasets is its longitudinal nature. Indeed, since 2003 systematic data collection ensures a consistent representativeness of the population of Spanish manufacturing and service firms over time, allowing to follow the same firms over a considerable number of years. This allows to control for unobserved factors that could have an impact on the relation between innovation variables and patterns of sales growth.

We select our working sample from an initial dataset of 100,016 firm-year observations over the period 2004-2011. We focus on manufacturing firms, and we look at "organic growth", hence discarding all firms involved in M&A events. The resulting sample is an unbalanced panel of 26,386 firm-year observations for which the variables used in our empirical exercise are non-missing. Table 1 shows

Table 1: Composition of the panel

Time obs.	#Firms	%	%Cum	#Obs.
3	140	2.76	2.76	140
4	230	4.54	7.31	460
5	250	4.94	12.24	750
6	328	6.48	18.72	1,312
7	972	19.19	37.91	4,860
8	3,144	62.09	100	18,864
Total	5,064	100		26,386

Note: "Time obs." indicate the minimum number of years over which firms are observed: T=3 refers to firms that are observed for at least three periods: T=4 corresponds to firms that are observed for at least four periods, and so on.

that the large majority of firms (62.09 %) is observed over the entire sample period, whereas another 19.19% persists in the data for 7 years, and only a negligible percentage (7,31%) for less than 5 years.

3.2 Main variables

Our dependent variable is firm growth measured in terms of sales. This is defined as the log-difference:

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

where

$$s_{it} = log(S_{it}) - \frac{1}{N}\sum_i log(S_{it}) \quad , \tag{2}$$

and S_{it} is sales (annual turnover) of firm i in year t, and the sum is computed over the N firms populating the same (2-digit) sector. In this way firm sizes and, thus, the growth rates are normalized by their annual sectoral average. The normalization implicitly removes common trends, such as inflation and business cycles effects in sectoral demand.

In our attempt to provide a multidimensional view about innovation activity of firms, we employ the following innovation indicators, available for each firm in each year:

1. *Internal R&D* (intensity): Intramural R&D expenditures, normalized by total turnover.
2. *External R&D* (intensity): Extramural R&D expenditures, normalized by total turnover.
3. *Prod New-to-the-firm*: Share of firm's total sales due to sale of new or significantly improved products, which are new only for the firm.
4. *Prod New-to-the-market*: Share in firm's total sales due to sales of new or significantly improved products, which are new to both the firm and the market.
5. *Process Innov*: Binary indicator equal to 1 if the firm introduces new or significantly improved processes, and 0 otherwise.

Table 2: Innovation variables - Descriptives

	Mean	Std.Dev.	Median	Min	Max
Internal R&D	0.031	0.161	0.004	0	7.986
External R&D	0.006	0.055	0	0	3.353
Prod. New-to-firm	0.248	0.352	0.056	0	1
Prod. New-to-MKT	0.099	0.225	0	0	1
Proc. Innov	0.633	0.482	1	0	1
Emb.Tech.Change	0.006	0.047	0	0	3.441
Disemb.Tech.Change	0.000	0.005	0	0	0.555

Notes: Figures computed pooling over the working sample - 26,386 observations.

6. *Embodied technological change* (intensity): Investment in innovative machinery and equipment, normalized by total turnover.

7. *Disembodied technological change* (intensity): Acquisition of external knowledge and technology (patents, know-how, etc., from other enterprises or organizations), normalized by total turnover.

The definitions of these proxies from PITEC are equivalent to their counterpart in innovation surveys from other countries. The interpretation is in most cases well accepted. R&D indicators just measure expenditures in different R&D activities, and we also follow the usual approach to take the ratio to total turnover instead of absolute figures. Concerning product innovation, the introduction of products perceived as new-to-the-market connects with the ability to perform more relevant innovation, resulting in more valuable products, while products new-to-the-firm are usually considered as a proxy of more "incremental" and less valuable innovation. The dummy for process innovation has the standard interpretation as capturing reorganization of production or implementation of new processes, and we also follow the common practice to interpret acquisition of new machineries and of external knowledge as proxies for, respectively, acquisition of embodied and disembodied technical change.

In Table 2 we report descriptive statistics for the innovation indicators. Notice, first, that all the indicators display highly skewed distributions, suggesting considerable heterogeneity in the innovative behavior. Second, firms in our sample appear more prone to undertake internal generation of knowledge rather than searching for external sources. Indeed, on average, intramural formalized R&D amounts to 3.1% of annual sales, while we observe an average 0.6% share in sales for both extramural R&D and for acquisition of innovative machineries and equipment, and such share is close to zero in the case of acquisition of disembodied knowledge. Further, from the indicators of innovative output, we see that a relatively large fraction of firms perform process innovation (around 63% of the observations). On the other hand, concerning product innovation, the share in total sales due to products new-to-the-market is on average smaller than the share of sales from products new-to-the-firms (9.9% vs. 24.8%). This hints that "truly" innovative products are more difficult to achieve and more rare than incremental innovation, and thus may contribute less to sales.

Table 3: Sales growth by innovation status - Descriptive statistics for

		Mean	Median	Min	Max	#Obs
Internal R&D	NO	-0.040	-0.016	-4.813	3.853	11,225
	YES	0.009	0.006	-3.821	4.674	15,161
External R&D	NO	-0.025	-0.008	-4.813	3.853	18,999
	YES	0.022	0.012	-3.821	4.674	7,387
Prod.New-to-firm	NO	-0.021	-0.007	-4.813	4.674	17,200
	YES	0.005	0.006	-3.603	3.57	9,186
Prod.New-to-MKT	NO	-0.027	-0.011	-4.813	4.674	10,237
	YES	-0.002	0.002	-3.958	3.57	16,149
Proc. Innov.	NO	-0.032	-0.016	-4.813	4.674	10,290
	YES	0.001	0.006	-3.958	3.57	16,096
Embod.Tech.Change	NO	-0.018	-0.006	-4.813	4.674	21,780
	YES	0.018	0.011	-2.839	3.253	4,606
Dis.Tech.Change	NO	-0.013	-0.003	-4.813	4.674	25,826
	YES	0.016	0.001	-2.759	2.615	560

Notes: descriptive statistics of G_t by "innovators" vs. "non-innovators" defined as firms that do (YES) or do not (NO) engage in innovation, according to the different innovation variables. Figures computed pooling over the working sample - 26,386 observations.

4 Descriptive evidence

As a first assessment of the relation between sales growth and innovation, we compare the growth rates across "innovators" and "non-innovators", that is splitting the sample between firms that do or do not undertake each specific innovative activity.[2]

In Table 3 we show basic descriptives of sales growth across the different subgroups. We see that "innovators" tend to display larger mean and median growth rates than "non-innovators", regardless the innovation variable. The median, in particular, is positive for "innovators" and negative for "non-innovators" for all the proxies.

In Figure 1 we report kernel estimates of the unconditional distribution of sales growth rates, again across "innovators" and "non-innovators". "Non-innovators" are generally more concentrated in the left part of the support, and these asymmetries are particularly pronounced for the two R&D indicators. Differences across the two groups are less clear-cut in the right tails, with the two distributions substantially overlapping, irrespective of the innovation variable considered. The visual inspection is complemented by a Fligner and Policello (1981) test of distributional equality (reported on the plots as FP), allowing to assess which of the two distributions stochastically dominates the other along each innovation variable considered. The null hypothesis of stochastic equality is always rejected (except for technological acquisition) and the positive FP statistics imply that "innovators" present a larger probability to experience superior growth performance than "non-innovators".

[2]Of course, non-innovators according to one variable may still be innovative firms, in the sense that they may be engaged in other types of innovative activity.

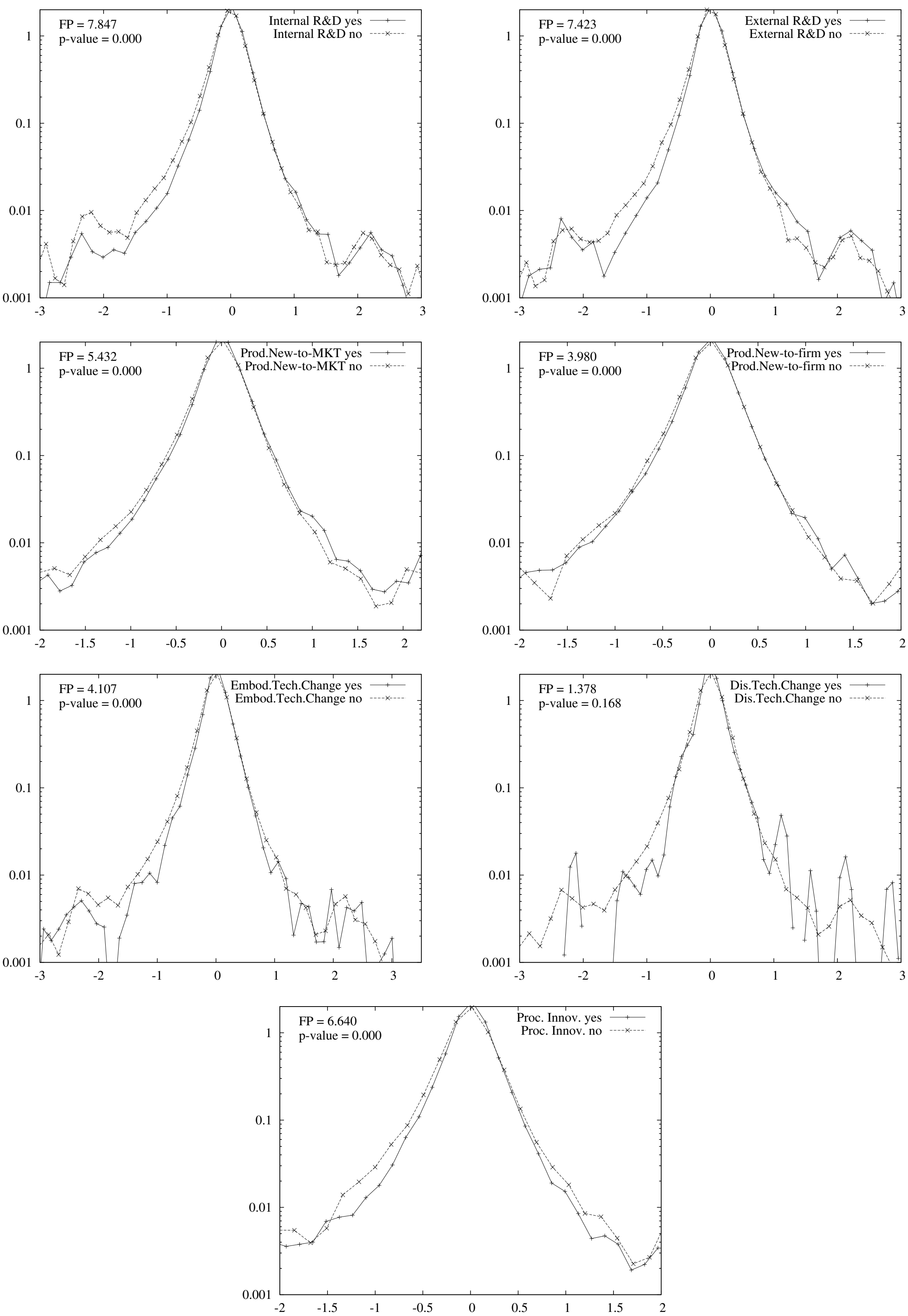

Figure 1: Kernel estimates (Epanenchnikov kernel) of sales growth rates densities for "innovators" vs. "non-innovators", defined as firms that do (YES) or do not (NO) engage in each innovation activity. Innovation proxies are Internal or External R&D (first row), Products new-to-the-firm or new-to-the-market (second row), Embodied vs. Disembodied technical change (third row), and Process Innovation (bottom row). Figures also report a Fligner and Policello (1981) test of stochastic dominance: a positive and significant FP statistic indicates that innovators dominate non-innovators along the innovation proxy considered. Results obtained pooling over the working sample - 26,386 observations.

Table 4: Descriptive statistics for the control variables

	Mean	Std.Dev.	Median	Min	Max
G_{t-1}	0.026	0.376	0.027	-4.813	4.739
$\ln Empl_{t-1}$	4.088	1.309	3.932	0	9.234
$\ln Age_{t-1}$	3.223	0.598	3.258	0	5.088
$Export_{t-1}$	0.796	0.403	1	0	1
$PubFund_{t-1}$	0.354	0.478	0	0	1
$Group_{t-1}$	0.378	0.485	0	0	1

Notes: Figures computed pooling over the working sample - 26,386 observations.

Overall, the distributional analysis suggests that innovators tend to be more able to avoid below-average growth rates, rather than to stably reach a positive and high-growth performance. Of course all these findings just provide an unconditional picture.

5 Regression analysis

In this Section we turn to regression analysis. The empirical strategy is to separately investigate the effect of each innovation activity, conditional on a set of controls. We first look at the effects on average growth, through standard panel techniques, and then exploit fixed-effects quantile regressions to explore the asymmetries in the innovation-growth relation across growing and shrinking firms.

The baseline empirical model is a panel regression equation

$$G_{i,t} = \alpha\ INNOV_{i,t-1} + \boldsymbol{\beta} \times \mathbf{Z_{i,t-1}} + u_i + \epsilon_{i,t} \quad , \tag{3}$$

where $INNOV$ stands alternatively for one of the different innovation variables, $\mathbf{Z}$ is a set of firm-level control variables, u_i is a firm fixed-effect, and $\epsilon_{i,t}$ a standard error term.

Both INNOV and the controls enter with a 1-year lag, at least partially controlling for potential simultaneity.[3] The set of controls includes the lagged dependent variable (G_{t-1}), a proxy for size in terms of number of employees (in logs, $\ln Empl$), firm age computed by year of foundation (in logs, $\ln Age$) and three dummy variables, respectively taking value 1 if firm i is exporting ($Export$), or receiving public financial support to innovation ($PubFund$), or belonging to an industrial group ($Group$) in year $t-1$, and zero otherwise.[4] All the specifications also include a full set of industry (2-digit) and year dummies. Table 4 reports basic descriptive statistics for the controls.

The coefficient of primer interest is of course α, capturing the effect of each specific innovation activity on sales growth. The inclusion of firm fixed-effects implies that identification works through

[3]Since one might argue that it takes time for innovation to be "translated" into sales growth, we also checked models including a full lag structure for the innovation variables. The baseline model with 1-year lag distance between $INNOV$ and growth was chosen through sequential rejection of the statistical significance of more distant lags.

[4]The $PubFund$ dummy records any kind of public financial support for innovation activities from Spanish local or government authorities and from the EU bodies, including tax credits or deductions, grants, subsidized loans, and loan guarantees. It excludes research and other innovation activities entirely conducted for the public sector under a specific contract.

within-firm changes of $INNOV$ proxies over time. This helps mitigating standard omitted variable bias, which in our case can provide a relatively severe source of incorrect estimation, due to the limited number of firm-level controls available in PITEC (as common also to other innovation surveys). In particular, we do not have data to compute a reliable measure of productivity, which is theoretically a crucial determinant of both growth and innovation, especially for its mediating role between input and output of innovation suggested by innovation studies. Firm fixed-effects absorb at least the time-invariant component of efficiency, while the time varying component remains unobserved and thus it is possibly interacting with other controls like age, size and export status. A similar reasoning applies to other unmeasured firm attributes that may jointly influence growth and innovation, such as financial constraints, managerial and organizational characteristics, or input quality. We however control for such sources of endogeneity via standard panel-GMM estimators. Conversely, quantile regression approaches jointly controlling for fixed effects and endogenous covariates are still under development.[5]

5.1 Panel estimates

We start presenting standard panel analysis of Equation (3). As a reference, we first show the results obtained with the Fixed Effects-Within (FE) estimator, although this might be severely biased due to endogeneity of regressors and the presence of the lagged dependent variable. Secondly, we apply the GMM-DIFF estimator (Arellano and Bond, 1991), that mitigates endogeneity via exploiting lags of the regressors as instruments after differencing the estimation equation.[6] The instruments included in the GMM procedure vary depending on the estimated equation. We always use $\ln Age$, $Group$ and year dummies as exogenous variables, while different lags of G, $INNOV$, $\ln Empl$, $Export$ and $PubFund$ are included, based on the standard Arellano-Bond tests for serial correlation and on Sargan/Hansen tests for overidentifying restrictions. We mainly comment on the GMM results, since these are in principle more reliable.

In Table 5 we show the models including the two measures of R&D intensity as innovation proxy. The FE results reveal a positive and strongly significant relation between sales growth and internal R&D intensity, whereas a much less significant association (at 10% level only) is detected with extra-mural R&D activity. The GMM estimates corroborate the results, and external R&D in this case looses statistical significance. The point estimates across the two estimation methods differ in magnitude, but cannot be considered as statistically different within 1-standard error confidence band. These findings confirm the central role of R&D as a driver of corporate growth and success on the market. At the same time, however, they suggest that it is internally developed research that pays off, while outsourced R&D does not support sales growth, on average at least.

Concerning the control variables, the estimated coefficients display robust patterns, irrespective of the innovation proxy considered. We comment on GMM results which tackles the good deal of endogeneity potentially affecting the analysis. First, we do not find any significant autocorrelation of sales growth over time. This is in line with the vast literature on size-growth relations and Gibrat's

[5] Harding and Lamarche (2009) and Harding and Lamarche (2014) are, to our knowledge, the only works tackling both fixed-effects and endogeneity at the same time. There are difficulties in implementing the methods, however, since one does not have an equivalent to panel-GMM allowing for internal instruments.

[6] We prefer this estimator over the alternative GMM-SYS estimator (Blundell and Bond, 1998) since firm growth is known to display weak persistence over time, and thus time-differences of growth are poor instruments for growth levels.

Table 5: Panel estimates - R&D intensity

	Innovation Proxy:			
	Internal R&D		External R&D	
	FE	GMM	FE	GMM
Dep.Var. is G_t	(1)	(2)	(3)	(4)
INNOV$_{t-1}$	0.2156***	0.3837***	0.4912*	0.5049
	(0.078)	(0.063)	(0.289)	(0.511)
G$_{t-1}$	-0.3087***	-0.2225	-0.3122***	-0.0534
	(0.013)	(0.178)	(0.012)	(0.155)
$\ln Empl_{t-1}$	-0.1605***	-0.1752	-0.1615***	-0.2010
	(0.022)	(0.229)	(0.022)	(0.199)
$\ln Age_t$	-0.1718***	-0.1888**	-0.1952***	-0.1933**
	(0.053)	(0.038)	(0.055)	(0.097)
$Export_{t-1}$	0.0037	-0.0801**	0.0034	-0.0779**
	(0.015)	(0.038)	(0.015)	(0.038)
$PubFund_{t-1}$	0.0014	-0.0076	0.0032	-0.0085
	(0.007)	(0.021)	(0.007)	(0.021)
$Group_{t-1}$	-0.0205	-0.0229	-0.0201	-0.0285
	(0.020)	(0.030)	(0.020)	(0.034)
Obs	26,386	21,291	26,386	21,291
AR(1)		0.016		0.001
AR(2)		0.600		0.518
Sargan		0.118		0.371
Hansen		0.333		0.370

Notes: Fixed Effects-Within (FE) and GMM-DIFF estimates of Equation (3). Regressions include a full set of year and sector dummies. Robust standard errors in parenthesis, clustered at firm-level: ***, ** and * indicate significance at 1%, 5% and 10% level, respectively. We also report p-values of Arellano-Bond test for first and second order serial correlation, AR(1) and AR(2), together with p-values of usual Sargan and Hansen tests for overidentifying restrictions.

law, where attempts to quantify growth rates autocorrelation provides quite mixed results, supporting the notion that growth follows a quite erratic and difficult to predict pattern. Second, and confirming one of the implications of Gibrat's Law, the coefficient on lagged size (in terms of employment) is not statistically different from zero. Third, age is always negatively correlated with firm growth, at strong significance level, confirming the intuition that younger firms are typically growing more rapidly than more mature firms. Fourth, export status has a negative and significant coefficient. This may be unexpected, since the literature on micro-empirics of exports suggest that exporters typically reach superior performance than non-exporters. Recall however that here the coefficient captures the effect of within-firm changes of export status over time, so that the result says that becoming exporters is associated to a reduction in sales growth. Finally, we observe a common pattern for the dummy variables identifying public support to innovation and group membership: both do not exert any statistically significant relation with sales growth.

Next, in Table 6, we present the estimates obtained with the indicators of product innovation, looking at shares of sales of products new-to the firm and of products new-to-the-market. Both

Table 6: Panel estimates - Product Innovation

	Innovation Proxy:			
	Prod.New-to-firm		Prod.New-to-MKT	
	FE	GMM	FE	GMM
Dep.Var. is G_t	(1)	(2)	(3)	(4)
INNOV$_{t-1}$	-0.0046	0.0771	0.0148	0.0464
	(0.009)	(0.048)	(0.014)	(0.030)
G$_{t-1}$	-0.3143***	-0.3129**	-0.3144***	-0.1112
	(0.012)	(0.156)	(0.012)	(0.157)
$\ln Empl_{t-1}$	-0.1620***	-0.4146**	-0.1620***	-0.2557
	(0.022)	(0.211)	(0.022)	(0.199)
$\ln Age_t$	-0.2079***	-0.3170***	-0.2083***	-0.2794***
	(0.057)	(0.082)	(0.057)	(0.074)
$Export_{t-1}$	0.0040	-0.1058***	0.0040	-0.0909**
	(0.015)	(0.039)	(0.015)	(0.038)
$PubFund_{t-1}$	0.0049	-0.0043	0.0045	0.0007
	(0.007)	(0.019)	(0.007)	(0.019)
$Group_{t-1}$	-0.0201	-0.0240	-0.0202	-0.0274
	(0.020)	(0.029)	(0.020)	(0.032)
Obs	26,386	21,291	26,386	21,291
AR(1)		0.021		0.002
AR(2)		0.377		0.761
Sargan		0.086		0.317
Hansen		0.336		0.261

Notes: Fixed Effects-Within (FE) and GMM-DIFF estimates of Equation (3). Regressions include a full set of year and sector dummies. Robust standard errors in parenthesis, clustered at firm-level: ***, ** and * indicate significance at 1%, 5% and 10% level, respectively. We also report p-values of Arellano-Bond test for first and second order serial correlation, AR(1) and AR(2), together with p-values of usual Sargan and Hansen tests for overidentifying restrictions.

variables turn out as not significant. The result is striking at first, since one expects the simple selling of new products should spur growth. But, what we measure here is whether the effect of an increase in the share of sales due to new products "translates" into an increase of overall sales. The result may suggest that this share is overall small and that only few new products have a deep impact on sales, so that in the end the contribution of product innovation vanishes, on average.

The results on the control variables (once again focusing on GMM estimates) are generally in agreement with the patterns emerged above in the models including internal and external R&D. The main difference is that in the specification with products new-to-the-firm, we find a negative autocorrelation of sales growth, and a negative effect of lagged size on subsequent sales growth. Both regressors loose their statistical significance in the model for share of sales due to products new-to-the-market. For all the other controls, point estimates and patterns of significance are similar across the two specifications . In line with the models including R&D variables, we confirm a negative and significant effect of age and export status, while the dummy variables indicating public support and group membership are confirmed to lack any statistically significant effect on sales growth.

Table 7 presents the estimates concerning the other innovation proxies. In columns 1-2 we exploit

Table 7: Panel estimates - Process Innov. and Embodied vs. Disembodied Tech. Change

	Innovation Proxy:					
	Proc. Innov.		Emb.Tech.Change		Dis.Tech.Change	
	FE	GMM	FE	GMM	FE	GMM
Dep.Var. is G_t	(1)	(2)	(3)	(4)	(5)	(6)
INNOV_{t-1}	-0.0001	0.0058	0.3499***	-0.0004	0.9572	0.4413
	(0.009)	(0.162)	(0.125)	(0.002)	(0.730)	(1.139)
G_{t-1}	-0.3143***	-0.0710	-0.3134***	-0.0633	-0.3144***	0.0497
	(0.012)	(0.199)	(0.012)	(0.050)	(0.012)	(0.092)
$\ln Empl_{t-1}$	-0.1621***	-0.1189	-0.1610***	-0.3686*	-0.1620***	-0.4371
	(0.022)	(0.235)	(0.022)	(0.204)	(0.022)	(0.295)
$\ln Age_t$	-0.2077***	-0.2782***	-0.2031***	-0.2528***	-0.2045***	-0.1979**
	(0.057)	(0.085)	(0.056)	(0.068)	(0.056)	(0.078)
$Export_{t-1}$	0.0040	-0.0814**	0.0036	-0.0968**	0.0040	-0.2175**
	(0.015)	(0.038)	(0.015)	(0.038)	(0.015)	(0.100)
$PubFund_{t-1}$	0.0048	0.0095	0.0032	-0.0091	0.0049	-0.0163
	(0.007)	(0.038)	(0.007)	(0.019)	(0.007)	(0.059)
$Group_{t-1}$	-0.0201	-0.0288	-0.0203	-0.0272	-0.0199	-0.0273
	(0.020)	(0.033)	(0.020)	(0.033)	(0.020)	(0.034)
Obs	26,386	21,291	26,386	21,291	26,386	21,291
AR(1)		0.006		0.000		0.000
AR(2)		0.678		0.115		0.048
Sargan		0.257		0.119		0.061
Hansen		0.164		0.271		0.353

Notes: Fixed Effects-Within (FE) and GMM-DIFF estimates of Equation (3). Regressions include a full set of year and sector dummies. Robust standard errors in parenthesis, clustered at firm-level: ***, ** and * indicate significance at 1%, 5% and 10% level, respectively. We also report p-values of Arellano-Bond test for first and second order serial correlation, AR(1) and AR(2), together with p-values of usual Sargan and Hansen tests for overidentifying restrictions.

the binary indicator for process innovation. Both FE and GMM results reveal that process innovation does not affect growth. The estimated coefficient are small and not significant. One explanation, already suggested above, is that process impacts on firm efficiency, rather than directly affecting sales growth. We thus observe here the result of a lacking relation between productivity and growth, recently suggested in several studies documenting that markets do not work as efficient selectors in redistributing market shares in favor of the more efficient firms (Bottazzi et al., 2008, 2010; Dosi et al., 2015).

Next, we find no statistically significant effect in the GMM estimates for the two proxies of external acquisition of embodied (columns 3-4) and disembodied technical change (columns 5-6). In line with the interpretation put forward above about the effect of external R&D, an explanation for the result calls for difficulties in managing the integration and the exploitation of knowledge and innovation sources acquired outside the boundaries of the firm. Or, again making a parallel between external R&D and acquisition of external knowledge, it may also be that firms tend to source from outside only marginal "ingredients" of their overall innovation process, such that the effect on sales growth is at best indirect and in the end nil.[7]

[7]Notice that in all the models of Table 7 the estimated coefficients on the control variables are broadly in line with

To sum up, the analyses deliver a negative result. The effect of innovation is, in general, quite modest. Once controlling for firm fixed-effects and endogeneity, only investing in R&D carried out internally stands out as a robust driver of subsequent sales growth. Of course, this conclusion only applies to the effect on the average of the conditional distribution. In this sense, our findings are not surprising, since they just extend to a large set of proxies of innovation the existing evidence that the very contribution of innovative activity may be to spur extreme growth events, rather than an effect on the average growth rate. The next Section explores exactly this issue via Fixed-Effects quantile regressions.

Another interpretation is that, since we exploit within-firm variation, the contribution to sales growth coming from innovation is related to the sticky components of innovation activities, washed away with firm fixed-effects. Consider, for instance, the lacking effect we find for sales due to new products. Our negative results would be explained by the fact that product innovators keep a relatively persistent share of sales due to new products, while non-innovators hardly can manage to become innovators over time. And a similar reasoning can be extended to the other innovation variables for which we do not find significant results. However, our intuition is that this explanation can play a role only in the case of the dummy indicator of process innovation, which is indeed fairly persistent, since "process innovators" and "process non-innovators" tend to remain like that over the sample period. All the other innovation proxies are instead continuous variables that change over time: for all of them, although there is some persistence, we have verified that there is also considerable within-firm variation.[8] Recall, finally, that we tested longer lag structures, so that the lacking effect estimated for most innovation variables cannot simply be explained by arguing that it takes more than one year for innovation to affect growth.

5.2 Fixed-Effects quantile regressions

The distributional analysis presented in Section 4 recalls one of the major stylized facts of industrial dynamics, stating that firm growth rates are characterized by a fat-tail distribution. This implies that standard regression analysis, capturing the effect on the expected value of the dependent variable, can only deliver a partial picture. Quantile regressions have become popular in recent years in the literature on firm growth and innovation to uncover possible asymmetric effects of innovation across the quantiles of the growth rates distribution.

We apply the fixed-effects quantile regression estimator developed in Canay (2011). The method consists of a transformation of the response variable that allows to "wash out" the firm fixed effect. First rewrite our baseline Equation (3) as

$$G_{i,t} = X'_{i,t-1}\beta + u_i + \epsilon_{i,t} \quad ,\text{with} \ \ E(\epsilon_{i,t}|X_i, u_i) = 0 \tag{4}$$

where the dependent is sales growth as defined above, $X_{i,t}$ contains the set of explanatory variables

the patterns observed above for the models using R&D and product innovation variables.

[8] As a further check that the results are not driven by too little within-firm variation of the innovation proxies, we also performed a Correlated Random Effects estimation, adding the within-firm time series averages of both innovation variables and controls as further regressors. The coefficient estimates on the lagged innovation regressors are by definition equivalent to the FE estimates reported above. The coefficient on the average components, capturing the time invariant part of innovation activities, is positive and significant for all the innovation proxies but for external R&D and disembodied technical change. Of course, Correlated Random Effects do not tackle endogeneity, however.

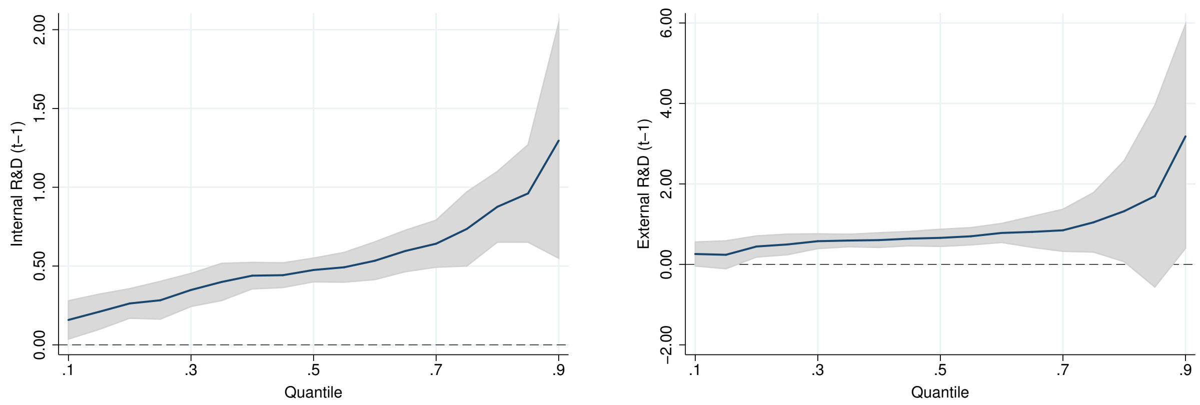

Figure 2: Fixed-Effects quantile regression estimates of coefficient α from Equation (3). Innovation proxies are Internal (left) and External (right) R&D intensity. The shaded areas represent 99% confidence band via bootstrapped standard errors.

(each innovation indicator $INNOV$, alternatively, plus the controls), while u_i and $\epsilon_{i,t}$ are the firm fixed-effect and the standard disturbance term.

Next, the Canay (2011) estimator proceeds in two steps: (i) obtain an estimate of the individual fixed effect through $\hat{u}_i = E_T[G_{i,t} - X'_{i,t-1}\hat{\beta}]$, where $E_T(.) = T^{-1}\sum_{t=1}^{T}(.)$ and $\hat{\beta}$ is the standard Fixed-Effects Within estimator of β; (ii) build a transformed response variable $\hat{G}_{i,t} = G_{i,t} - \hat{u}_i$ and then obtain quantile regression coefficients through

$$\hat{\beta}(\tau) = \underset{\beta \in B}{\operatorname{argmin}} E_{nT}\left[\rho_\tau\left(\hat{G}_{i,t} - X'_{i,t-1}\beta\right)\right] \ , \tag{5}$$

which is just a quantile regression as in Koenker and Bassett (1978) on the transformed dependent variable. Notice that, since much like in standard regressions, fixed-effects might exacerbate the bias due to the presence of the lagged dependent among the regressors, we estimate a static version of the baseline model, without the autoregressive term G_{t-1}.

In line with the standard panel regression of the previous Section, we estimate our baseline model separately for each innovation variable. In Figure 2, 3 and 4 we provide a graphical representation of the results, plotting the coefficient associated to the different innovation variables across the quantiles of the growth rates distribution.[9] To evaluate statistical significance, we also show a 99% confidence band, obtained from bootstrapped standard errors, as recommended in Koenker (2004) and Canay (2011).

Figure 2 shows the results for internal and external R&D. We find evidence of clearcut heterogeneities in the effects of each indicator across the growth rates distribution. Two results are worth noticing here, common across the two proxies. First, the coefficients are positive and significantly different from zero for both variables in practically all the quantiles. The estimated coefficient on external R&D is twice as larger, but so is the standard error. Second, the coefficient estimates are smaller for shrinking firms or slow-growing firms, in the bottom quantiles, and then they steadily moving towards the top quantiles. That is, R&D activities provide a stronger contribution to growth performance of high-growth firms. These asymmetries are open to different interpretations. On the

[9]See the tables in Appendix for full set of coefficient estimates.

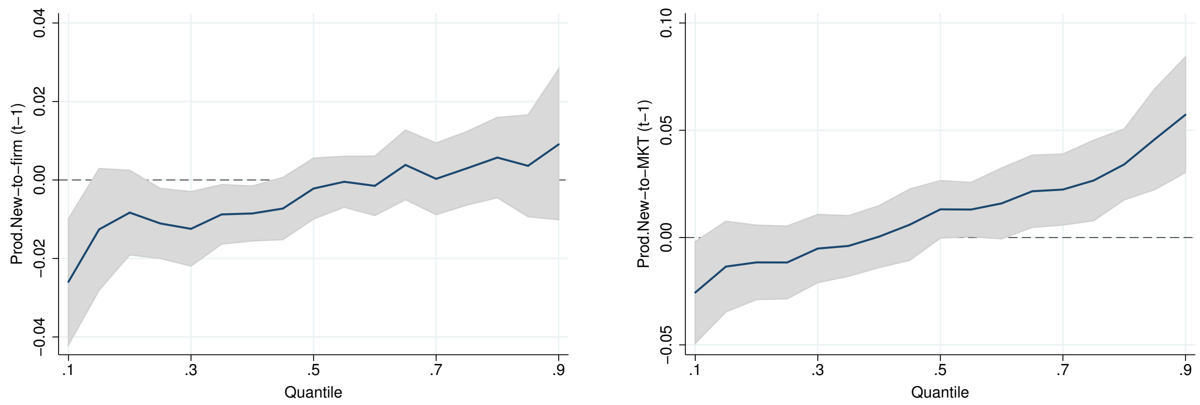

Figure 3: Fixed-Effects quantile regression estimates of coefficient α from Equation (3). Innovation proxies are % of sales due to products new-to-the-firm (left) and % of sales due to products new-to-the-market (right). Shaded areas represent 99% confidence band via bootstrapped standard errors.

one hand, connecting to uncertainty of exploration and exploitation, our findings imply that shrinking and "normal-growing" firms are more often engaged in R&D efforts that do not turn into success. On the other hand, it may be that R&D brings successful outcomes even for these less-performing firms, but then these firms are less able than high-growth firms to seize the returns to R&D in terms of markets shares, due to, for instance, a generally weak competitiveness.

We comment on the effects of product innovation variables in Figure 3. Overall, sales due to products new-to-the-market shows a statistically significant association with sales growth starting from the median of the growth rate distribution, with the largest magnitude in the top quantiles. This implies that product innovation is particularly relevant for high-growth. Conversely, the estimates of the effect of sales due to products new-to-the-firm reveal do not show any statistical significance in the right part of the growth rates distribution. Actually, there is a peculiar behavior in the left side of the support, namely negative and strongly significant estimated coefficients across shrinking firms. A tentative interpretation is that, despite such firms try and readjust their product range through imitative and incremental innovations, the competitive pressure is however too strong and hampers any recovery in sales market shares.

The results of regressions with embodied and disembodied technical change are reported in the top plots of Figure 4. The estimated coefficients for embodied technical change tend to be small or not even significant in the bottom quantiles, and then become positive and significant starting from the median and through the upper quantiles. The pattern mimics what observed for R&D and product innovation (new-to-the-market, in particular), thus confirming the generally more crucial importance of innovation activities for high-growth firms. Conversely, disembodied technical change does not show any significant coefficient across the entire spectrum of the growth rates distribution. The already mentioned explanations related to lacking absorptive capacity and complex interactions between external sourcing and growth certainly play a role here.

The same negative results applies to the relation between growth and process innovation, depicted in the bottom plot of Figure 4, where we indeed do not observe any significant coefficient along the growth rates quantiles. If anything, there is a mild negative effect among top-growing firms.

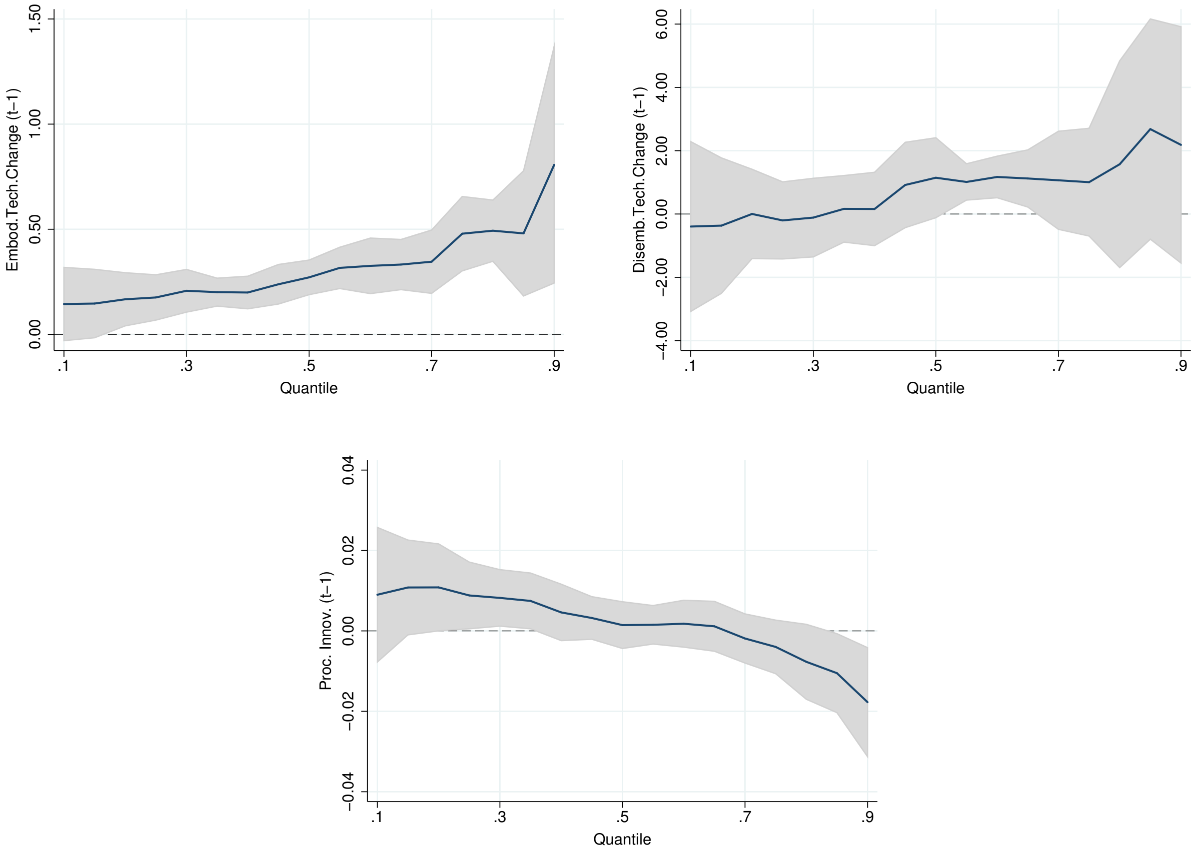

Figure 4: Fixed-Effects quantile regression estimates of coefficient α from Equation (3). Innovation proxies are Embodied (top-left) vs. Disembodied (top-right) technical change, and Process Innovation (bottom). Shaded areas represent 99% confidence band via bootstrapped standard errors.

Overall, fixed-effects quantile regressions allow for two major qualifications of the standard panel analysis. First, the positive effect of internal R&D on growth is confirmed, but we discover that it actually originates for the most part from growing and fast-growing firms. Second, we find that some of the innovation variables which do not affect average growth do have, instead, a positive and significant effect on sales growth of high-growth firms in the top quantiles. This is the case for external R&D, for product innovation (new-to-the-market) and also for technical change embodied in the acquisition of new machineries. We instead fully confirm the irrelevance of process innovation and disembodied technical change in fostering growth.

6 Complementarities between innovation activities

Firms in reality often undertake different innovation activities at the same time. In this Section we explore if sales growth originates from combinations of different innovation activities, rather than from each single one.

Our key question is whether different innovation activities are complements in their effect on growth. We explore this issue through the concept of super-modularity. In general terms, consider a function $f(\mathbf{X})$, where $\mathbf{X}$ is a vector of binary arguments, $\mathbf{X}$=$\{X_1, X_2, \ldots, X_n\}$, with $X_j = \{0, 1\}$

depending whether a certain action j is undertaken or not. Action X_j and X_i are complements if f is super-modular in X_j and X_i, that is

$$f(X_j \vee X_i) + f(X_j \wedge X_i) \geq f(X_j^c) + f(X_i^c) \quad , \tag{6}$$

where A^c stands for "non-A".

The idea is simply that the effect of choosing X_j on the objective function f is larger if also X_i is chosen at the same time, as compared to other possible combinations where X_j appears, while X_i is not chosen. We apply this framework to explore the super-modularity of the growth function with respect to a set of innovation activities.

We proceed as follows. Firstly, we group our original seven innovation indicators into four categories, capturing the different types of innovation output (product or process) and the different innovation inputs distinguishing between internal R&D and external sources. Accordingly, we define the following dummy variables for each year:

- Internal innovation (INT) = 1 if the firm performs intra-mural R&D, and 0 otherwise.
- External innovation (EXT) = 1 if the firm performs extra-mural R&D or acquires embodied or disembodied knowledge, and 0 otherwise.
- Product innovation (NEWP) = 1 if the firms introduces products new-to-the-market, and 0 otherwise.
- Process innovation (PROC) = 1 if the firms introduces new or significantly improved processes, and 0 otherwise.

Of course, firms may engage in none, just one or more of these activities at the same time. The four basic activities may be combined in $2^4 = 16$ different possible combinations, that we label "innovation strategies". These are listed in Table 8. So, for instance, STR_0 is a dummy that takes value 1 if a firm does not engage in any of the four basic activities. This is also conventionally indicated as S_{0000}. STR_1 is a strategy where a firm only engages in process innovation (S_{0001}), and so on.

Next, we specify the growth function as a regression of sales growth against the set of alternative strategies

$$G(S, \mathbf{Z}) = f(S_{0001}, S_{0010}, ..., S_{1111}, \mathbf{Z}), \tag{7}$$

where the dependent G is sales growth, $\mathbf{Z}$ is our set of lagged controls (including lagged growth, size, age, export status, public finance and group membership) as in the main Equation (3), and we normalize S_{0000} to zero. Notice that the strategy dummies are measured in $t-1$ and can change over time.

The definition of super-modularity of G with respect to the lattice S means that

$$G(S' \vee S'', \mathbf{Z}) + G(S' \wedge S'', \mathbf{Z}) \geq G(S', \mathbf{Z}) + G(S'', \mathbf{Z}) \quad . \tag{8}$$

The number of non trivial inequalities implied by this definition is $2^{(K-2)} \sum_{i=1}^{K-1} i$, where K is the number of basic categories for which one wants to assess pairwise complementarity (Topkis, 1998). In our case, $K = 4$ and we thus have a total of 24 nontrivial inequality constraints, 4 for each pairwise

Table 8: Innovation strategies

Strategy	INT	EXT	NEWP	PROC	Combination
STR_0	0	0	0	0	No inno
STR_1	0	0	0	1	PROC
STR_2	0	0	1	0	NEWP
STR_3	0	0	1	1	NEWP&PROC
STR_4	0	1	0	0	EXT
STR_5	0	1	0	1	EXT&PROC
STR_6	0	1	1	0	EXT&NEWP
STR_7	0	1	1	1	EXT&NEWP&PROC
STR_8	1	0	0	0	INT
STR_9	1	0	0	1	INT&PROC
STR_{10}	1	0	1	0	INT&NEWP
STR_{11}	1	0	1	1	INT&NEWP&PROC
STR_{12}	1	1	0	0	INT&EXT
STR_{13}	1	1	0	1	INT&EXT&PROC
STR_{14}	1	1	1	0	INT&EXT&NEWP
STR_{15}	1	1	1	1	INT&EXT&NEWP&PROC

combination of basic innovation activities. Labeling as b_j the coefficient on the dummy STR_j estimated from Equation (7), the constraints can be compactly written as:

- Complementarity INT-EXT: $b_{8+s} + b_{4+s} \leq b_{0+s} + b_{12+s}$ with $s = 0, 1, 2, 3$
- Complementarity INT-NEWP: $b_{8+s} + b_{2+s} \leq b_{0+s} + b_{10+s}$ with $s = 0, 1, 4, 5$
- Complementarity INT-PROC: $b_{8+s} + b_{1+s} \leq b_{0+s} + b_{9+s}$ with $s = 0, 2, 4, 6$
- Complementarity EXT-NEWP: $b_{4+s} + b_{2+s} \leq b_{0+s} + b_{6+s}$ with $s = 0, 1, 8, 9$
- Complementarity EXT-PROC: $b_{4+s} + b_{1+s} \leq b_{0+s} + b_{5+s}$ with $s = 0, 2, 8, 10$
- Complementarity NEWP-PROC: $b_{2+s} + b_{1+s} \leq b_{0+s} + b_{3+s}$ with $s = 0, 4, 8, 12$

For each pair, the constraints must hold jointly. To implement the test, we exploit the Wald-type statistic and the procedure derived in Kodde and Palm (1986). Let $\gamma = (b_{0001}, b_{0010}, ..., b_{1111})'$ be the coefficients to be estimated from the growth function in (7). Then, the test statistic is given as

$$D = (C\tilde{\gamma} - C\hat{\gamma})'(C'cov(\hat{\gamma})C)^{-1}(C\tilde{\gamma} - C\hat{\gamma}) \tag{9}$$

with

$$\tilde{\gamma} = \underset{\gamma}{\operatorname{argmin}}(C\gamma - C\hat{\gamma})'(C'cov(\hat{\gamma})C)^{-1}(C\gamma - C\hat{\gamma}) \quad s.t. \quad C\gamma \leq 0 \tag{10}$$

where $\hat{\gamma}$ is the estimate of γ from the growth function in (7) and $cov(\hat{\gamma})$ the associated covariance matrix, while C is a matrix that maps the coefficients into the inequality constraints stated above. The set of coefficient $\tilde{\gamma}$ is obtained as the closest value to the estimates of γ under the restrictions imposed by the matrix C, and it can be computed via quadratic minimization under inequality constraints. The D statistic does not have an exact distribution, but Kodde and Palm (1986) provide lower and upper bounds for different levels of significance. The null of complementarity is accepted for values of D below the lower bound and it is rejected for values above the upper bound, whereas the test is inconclusive if the estimated D falls in between the two bounds.

The main requirement for the procedure to work is that $\hat{\gamma}$ is a consistent estimate of γ. Thus, we estimate the growth function via the GMM-DIFF estimator. This allows, once again, to control for firm fixed-effects and endogeneity of innovation strategies and controls.

Results are presented in Table 9. In the left panel we show the estimates of the growth function. The set of instruments includes lags of growth and controls, as well as lag-2 of the innovation strategies in the set S. The coefficients on the strategies are all positive, but most of them are not significant, except for STR_4 (i.e., EXT alone), STR_8 (INT alone), STR_{10} (combination of INT and NEWP), and STR_{13} (INT+EXT+PROC). The coefficients as such convey little information, as they do not provide a formal test of complementarity. The super-modularity tests are presented in the right panel. We show the estimated D statistic for the different pairwise combinations of the basic innovation activities. We report in bold the combinations where the null of complementarity cannot be rejected at the 10% level, which is the standard significance level in previous studies exploiting our methodology.

Results support complementarity only in two cases. First, we find evidence of complementarity between INT and NEWP, implying that these two activities exerts a super-additive effect in terms of sales growth. We therefore confirm the crucial role of internal R&D, but we can add that internal R&D pays more in terms of growth when it is coupled with the introduction of new products. The other side of the coin in reading of the result is that the introduction of new products (new-to-the-market) per se impact less on growth when undertaken alone than when undertaken jointly with formal R&D carried out internally.

Second, there is complementarity between process and product innovation. This result, on the one hand, further highlights that product innovation is more beneficial when coupled with other activities, as we just saw for its combination with internal R&D. On the other hand, we recover here a role for process innovation. While in the panel and quantile analysis we concluded that process innovation alone does not directly affect growth, we now find that restructuring of production processes is effective if combined with product innovation (in products new-to-the-market). Conversely, process innovation is not complement nor with internal R&D, neither with external innovation.

Indeed, we do not detect any complementarity of external sourcing of knowledge with none of the other innovation activities. This finding once again recall the already emerged difficulties in integrating knowledge and technologies produced outside the firm, due to, e.g., complex coordination with external "providers" or to weak absorptive capacity. In this respect, the analysis of complementarity confirms the conclusion emerging from the analysis of the separate role of external R&D and of embodied and disembodied technical change.

Table 9: Estimation results & complementarity test

	Estimation	Complementarity test	
Dep.Var. is G_t	(1)	Pair	Wald statistic
$\mathrm{STR}_{1,t-1}$	0.0293	INT-EXT	5.3215
	(0.063)	INT-NEWP	**1.6045**
$\mathrm{STR}_{2,t-1}$	0.0769	INT-PRO	4.8413
	(0.147)	EXT-NEWP	3.0288
$\mathrm{STR}_{3,t-1}$	0.1986	EXT-PRO	6.0155
	(0.155)	NEWP-PRO	**1.6156**
$\mathrm{STR}_{4,t-1}$	0.4623**		
	(0.208)		
$\mathrm{STR}_{5,t-1}$	0.0309		
	(0.080)		
$\mathrm{STR}_{6,t-1}$	-0.1448		
	(0.454)		
$\mathrm{STR}_{7,t-1}$	0.1330		
	(0.140)		
$\mathrm{STR}_{8,t-1}$	0.1798**		
	(0.090)		
$\mathrm{STR}_{9,t-1}$	0.0300		
	(0.102)		
$\mathrm{STR}_{10,t-1}$	0.1849*		
	(0.105)		
$\mathrm{STR}_{11,t-1}$	0.1464		
	(0.114)		
$\mathrm{STR}_{12,t-1}$	0.0886		
	(0.123)		
$\mathrm{STR}_{13,t-1}$	0.1888**		
	(0.095)		
$\mathrm{STR}_{14,t-1}$	0.2091		
	(0.129)		
$\mathrm{STR}_{15,t-1}$	0.1160		
	(0.104)		
G_{t-1}	-0.3042***		
	(0.092)		
$\ln Empl_{t-1}$	-0.1279		
	(0.180)		
$\ln Age_t$	-0.3182***		
	(0.074)		
$Export_{t-1}$	-0.2848**		
	(0.120)		
$PubFund_{t-1}$	0.0324		
	(0.069)		
$Group_{t-1}$	-0.0323		
	(0.031)		
Obs	21,291		
AR(1)	0.000		
AR(2)	0.133		
Sargan	0.120		
Hansen	0.131		

Notes: GMM-DIFF estimates of Equation (7). Regression includes a full set of year dummies. Robust standard errors in parenthesis, clustered at firm-level: ***, ** and * indicate significance at 1%, 5% and 10% level, respectively. We also report p-values of Arellano-Bond test for first and second order serial correlation, AR(1) and AR(2), together with p-values of usual Sargan and Hansen tests for overidentifying restrictions.

Complementarity test: bold values indicate acceptance of complementarity at 10% significance level (lower bound = 1.642, upper bound = 7.094).

7 Conclusions

The relation between innovation and firm growth has for long interested economists. While theory tends to predict a strong positive link, the empirical literature provides mixed results. Moreover, despite the multifaceted and complex nature of innovation is often recognized, there is a disproportionate tendency to look at traditional measures of innovative activity such as R&D and patents.

This paper, by taking advantage of a rich panel on innovation activity of Spanish manufacturing firms, provides new insights on the relations between success on the market, in terms of sales growth, and a richer set of innovation dimensions, capturing innovation inputs and outputs as well as different modes of sourcing new knowledge.

The overall picture emerging from the analysis suggests a good deal of heterogeneity in the capacity of different innovation activities to support expansion of sales and market shares.

First, from standard panel regression analysis, controlling for firm fixed-effects and endogeneity, we find that internal R&D is the only innovation indicator significantly (and positively) related with sales growth. Conversely, we do not find any statistically significant relation between growth and external R&D, process innovation, sales due to new products, as well as no effect is detected for acquisitions of embodied or disembodied new technologies. This negative result is striking, at first, but there are explanations for some of the findings. The lacking correlation between external sourcing of new knowledge or new technologies (external R&D, purchases of disembodied and embodied technical change) supports the view that valuable knowledge is inherently firm-specific. Firms may face difficulties in establishing effective collaboration with external providers, or may lack of specific absorptive capacities in integrating external knowledge and technologies within the firm. The equally lacking effect of process innovation can be interpreted as a signal that new processes are primarily designed to improve efficiency or to change production modes, and may affect sales growth only indirectly and in later stages. And, finally, the weak role of product innovation may just reflect that the share of sales due to new products is on average small. Overall, we confirm previous studies that highlight how the effect of innovation activities on average growth may be difficult to detect.

Second, we recover a positive effect for most of the innovation variables when we look at their association with growth along the quantiles of the growth rates distribution. Fixed-effects quantile regressions show that most innovation variables, with the exception of process innovation and disembodied technical change, have a positive and significant association with growth in the top quantiles, that is for high-growth firms. This result adds to the emerging literature underlying the peculiarities of high-growth firms, which has so far explored a more limited set of innovation indicators (R&D and patents) as drivers of growth, and generally without controlling for unobserved heterogeneity.

Finally, the analysis of the complementarities between innovation activities adds further insights. We confirm the importance of internal R&D as a driver of sales growth, but we also find that also product and process innovation represent sources of relevant complementarities. Indeed, we find that the beneficial effect of internal R&D on sales growth is stronger when coupled with product innovation, and that process and product innovation have a stronger association with growth if carried out jointly than alone. Therefore, a mix of R&D and product innovation, as well as a mix of process and product innovation emerge as the two more valuable strategies, providing a stronger positioning that allow firms to expand their market shares.

The research agenda is of course open to further developments, in particular to extend the analysis on the interactions among different innovation activities we consider here. We foresee many possible extensions. First, perhaps with richer datasets longer in time, one might identify the effect of sequential adoption of basic innovation strategies, exploring in more details whether, e.g., acquisition of new machineries turns out to have a positive impact on growth only after a subsequent process innovation related to that acquisition is implemented. Or, second, although our analysis of complementarities already incorporates the idea that firms engage in a different number and in different types of basic innovation activities, one can imagine to deepen the analysis of the relation between growth and the degree of "complexity" of firm's innovation strategies. For instance, one may think of taxonomies seeking to characterize complexity in terms of some measure of the coherence among the different innovation activities performed within each firm, and assess whether this translates into differential patterns of growth. Our results, so far, suggest that a combination of internal R&D, process and product innovation is the key candidate to provide the more effective mix of growth-enhancing strategies, especially in view of their observed strong relation with high-growth episodes.

Appendix

For completeness, we present tables reporting all the coefficient estimates from fixed-effects quantile regressions applied to our baseline model as Section 5.2. Graphical representation of the results obtained for each innovation variable, and related comments, are presented in the main text.

Table 10: Quantile regressions – Internal R&D

	Quantile (%)				
	10	25	50	75	90
Internal R&D$_{t-1}$	0.158***	0.283***	0.475***	0.735***	1.296***
	(0.051)	(0.061)	(0.031)	(0.105)	(0.288)
$\ln Empl_{t-1}$	-0.193***	-0.209***	-0.222***	-0.235***	-0.250***
	(0.003)	(0.002)	(0.001)	(0.002)	(0.003)
$\ln Age_t$	-0.071***	-0.088***	-0.101***	-0.113***	-0.129***
	(0.005)	(0.003)	(0.002)	(0.003)	(0.005)
$Export_{t-1}$	0.047***	0.022***	0.009***	-0.002	-0.014
	(0.009)	(0.004)	(0.003)	(0.005)	(0.009)
$PubFund_{t-1}$	-0.000	-0.003	-0.008***	-0.004	-0.014*
	(0.006)	(0.003)	(0.002)	(0.003)	(0.007)
$Group_{t-1}$	-0.045***	-0.029***	-0.019***	-0.008**	0.018**
	(0.006)	(0.004)	(0.003)	(0.004)	(0.008)
Observations	26,386	26,386	26,386	26,386	26,386
Industry dummies	Yes	Yes	Yes	Yes	Yes
Time dummies	Yes	Yes	Yes	Yes	Yes

Notes: Fixed-effects quantile regression estimates of Equation (3). Bootstrapped standard errors in parenthesis. ***, ** and * indicate significance on a 1%, 5% and 10% level, respectively.

Table 11: Quantile regressions – External R&D

	Quantile (%)				
	10	25	50	75	90
External R&D$_{t-1}$	0.258*	0.495***	0.659***	1.046***	3.182**
	(0.135)	(0.147)	(0.100)	(0.276)	(1.373)
$\ln Empl_{t-1}$	-0.194***	-0.212***	-0.225***	-0.238***	-0.256***
	(0.003)	(0.002)	(0.001)	(0.001)	(0.003)
$\ln Age_t$	-0.102***	-0.121***	-0.136***	-0.148***	-0.167***
	(0.005)	(0.003)	(0.002)	(0.003)	(0.005)
$Export_{t-1}$	0.049***	0.021***	0.009***	-0.001	-0.017*
	(0.009)	(0.004)	(0.003)	(0.005)	(0.009)
$PubFund_{t-1}$	-0.002	-0.002	-0.002	0.004	-0.002
	(0.006)	(0.003)	(0.002)	(0.003)	(0.008)
$Group_{t-1}$	-0.046***	-0.029***	-0.020***	-0.009**	0.017**
	(0.006)	(0.004)	(0.003)	(0.004)	(0.008)
Observations	26,386	26,386	26,386	26,386	26,386
Industry dummies	Yes	Yes	Yes	Yes	Yes
Time dummies	Yes	Yes	Yes	Yes	Yes

Notes: Fixed-effects quantile regression estimates of Equation (3). Bootstrapped standard errors in parenthesis. ***, ** and * indicate significance on a 1%, 5% and 10% level, respectively.

Table 12: Quantile regressions – Prod.New-to-firm

	Quantile (%)				
	10	25	50	75	90
Prod.New-to-firm$_{t-1}$	-0.026***	-0.011***	-0.002	0.003	0.009
	(0.008)	(0.004)	(0.004)	(0.005)	(0.008)
$\ln Empl_{t-1}$	-0.193***	-0.212***	-0.225***	-0.240***	-0.258***
	(0.003)	(0.002)	(0.001)	(0.001)	(0.003)
$\ln Age_t$	-0.114***	-0.135***	-0.150***	-0.163***	-0.183***
	(0.005)	(0.003)	(0.002)	(0.003)	(0.005)
$Export_{t-1}$	0.049***	0.022***	0.009***	-0.000	-0.019**
	(0.009)	(0.004)	(0.003)	(0.004)	(0.010)
$PubFund_{t-1}$	-0.003	-0.001	-0.002	0.007***	0.013**
	(0.006)	(0.003)	(0.003)	(0.003)	(0.006)
$Group_{t-1}$	-0.048***	-0.030***	-0.019***	-0.008**	0.015*
	(0.006)	(0.004)	(0.003)	(0.004)	(0.008)
Observations	26,386	26,386	26,386	26,386	26,386
Industry dummies	Yes	Yes	Yes	Yes	Yes
Time dummies	Yes	Yes	Yes	Yes	Yes

Notes: Fixed-effects quantile regression estimates of Equation (3). Bootstrapped standard errors in parenthesis. ***, ** and * indicate significance on a 1%, 5% and 10% level, respectively.

Table 13: Quantile regressions – Prod.New-to-MKT

	Quantile (%)				
	10	25	50	75	90
Prod.New-to-MKT$_{t-1}$	-0.026**	-0.012*	0.013**	0.027***	0.057***
	(0.013)	(0.007)	(0.006)	(0.009)	(0.013)
$\ln Empl_{t-1}$	-0.193***	-0.212***	-0.226***	-0.240***	-0.258***
	(0.003)	(0.002)	(0.001)	(0.001)	(0.003)
$\ln Age_t$	-0.115***	-0.135***	-0.150***	-0.164***	-0.182***
	(0.005)	(0.003)	(0.002)	(0.003)	(0.004)
$Export_{t-1}$	0.050***	0.023***	0.010***	-0.000	-0.019**
	(0.009)	(0.005)	(0.003)	(0.004)	(0.009)
$PubFund_{t-1}$	-0.003	-0.001	-0.002	0.007***	0.011*
	(0.006)	(0.003)	(0.002)	(0.003)	(0.006)
$Group_{t-1}$	-0.048***	-0.030***	-0.020***	-0.008**	0.015**
	(0.006)	(0.004)	(0.003)	(0.004)	(0.007)
Observations	26,386	26,386	26,386	26,386	26,386
Industry dummies	Yes	Yes	Yes	Yes	Yes
Time dummies	Yes	Yes	Yes	Yes	Yes

Notes: Fixed-effects quantile regression estimates of Equation (3). Bootstrapped standard errors in parenthesis. ***, ** and * indicate significance on a 1%, 5% and 10% level, respectively.

Table 14: Quantile regressions – Process Innovation dummy

	Quantile (%)				
	10	25	50	75	90
Proc. Innov$_{t-1}$	0.009	0.009***	0.001	-0.004	-0.018**
	(0.007)	(0.003)	(0.002)	(0.003)	(0.007)
$\ln Empl_{t-1}$	-0.193***	-0.213***	-0.226***	-0.240***	-0.259***
	(0.003)	(0.002)	(0.001)	(0.001)	(0.003)
$\ln Age_t$	-0.114***	-0.134***	-0.150***	-0.164***	-0.182***
	(0.005)	(0.003)	(0.002)	(0.003)	(0.005)
$Export_{t-1}$	0.048***	0.021***	0.010***	0.001	-0.011
	(0.010)	(0.005)	(0.003)	(0.005)	(0.010)
$PubFund_{t-1}$	-0.007	-0.002	-0.002	0.008***	0.017***
	(0.006)	(0.003)	(0.002)	(0.003)	(0.006)
$Group_{t-1}$	-0.048***	-0.030***	-0.019***	-0.008**	0.018**
	(0.006)	(0.004)	(0.003)	(0.004)	(0.008)
Observations	26,386	26,386	26,386	26,386	26,386
Industry dummies	Yes	Yes	Yes	Yes	Yes
Time dummies	Yes	Yes	Yes	Yes	Yes

Notes: Fixed-effects quantile regression estimates of Equation (3). Bootstrapped standard errors in parenthesis. ***, ** and * indicate significance on a 1%, 5% and 10% level, respectively.

Table 15: Quantile regressions – Embod.Tech.Change

	Quantile (%)				
	10	25	50	75	90
Emb.Tech.Change$_{t-1}$	0.144	0.176**	0.271***	0.479***	0.806***
	(0.090)	(0.084)	(0.066)	(0.104)	(0.301)
ln $Empl_{t-1}$	-0.192***	-0.211***	-0.225***	-0.239***	-0.258***
	(0.003)	(0.002)	(0.001)	(0.001)	(0.003)
ln Age_t	-0.111***	-0.131***	-0.145***	-0.159***	-0.181***
	(0.005)	(0.003)	(0.002)	(0.003)	(0.005)
$Export_{t-1}$	0.046***	0.021***	0.008**	-0.001	-0.019**
	(0.009)	(0.005)	(0.003)	(0.005)	(0.010)
$PubFund_{t-1}$	-0.003	-0.002	-0.002	0.007**	0.010
	(0.006)	(0.003)	(0.002)	(0.003)	(0.006)
$Group_{t-1}$	-0.047***	-0.029***	-0.019***	-0.007**	0.018**
	(0.006)	(0.004)	(0.003)	(0.004)	(0.008)
Observations	26,386	26,386	26,386	26,386	26,386
Industry dummies	Yes	Yes	Yes	Yes	Yes
Time dummies	Yes	Yes	Yes	Yes	Yes

Notes: Fixed-effects quantile regression estimates of Equation (3). Bootstrapped standard errors in parenthesis. ***, ** and * indicate significance on a 1%, 5% and 10% level, respectively.

Table 16: Quantile regressions – Disemb.Tech.Change

	Quantile (%)				
	10	25	50	75	90
Dis.Tech.Change$_{t-1}$	-0.395	-0.202	1.146*	1.006	2.184
	(1.476)	(0.907)	(0.632)	(1.006)	(2.259)
ln $Empl_{t-1}$	-0.194***	-0.212***	-0.226***	-0.240***	-0.259***
	(0.003)	(0.002)	(0.001)	(0.001)	(0.003)
ln Age_t	-0.112***	-0.132***	-0.147***	-0.161***	-0.181***
	(0.005)	(0.003)	(0.002)	(0.003)	(0.005)
$Export_{t-1}$	0.046***	0.022***	0.009***	-0.000	-0.021**
	(0.009)	(0.004)	(0.003)	(0.005)	(0.009)
$PubFund_{t-1}$	-0.003	-0.002	-0.002	0.008***	0.014**
	(0.006)	(0.003)	(0.002)	(0.003)	(0.006)
$Group_{t-1}$	-0.046***	-0.029***	-0.019***	-0.008**	0.017**
	(0.006)	(0.004)	(0.003)	(0.004)	(0.008)
Observations	26,386	26,386	26,386	26,386	26,386
Industry dummies	Yes	Yes	Yes	Yes	Yes
Time dummies	Yes	Yes	Yes	Yes	Yes

Notes: Fixed-effects quantile regression estimates of Equation (3). Bootstrapped standard errors in parenthesis. ***, ** and * indicate significance on a 1%, 5% and 10% level, respectively.

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