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Innovation Strategies and Firm Growth: New Longitudinal Evidence from Spanish Firms

Stefano Bianchini
Strasbourg
BETA
bianchini.stfn@gmail.com

Gabriele Pellegrino
Sussex
SPRU
gabriele-pellegrino@hotmail.it

Federico Tamagni
Scuola Superiore Sant'Anna, Pisa
Institute of Economics
f.tamagni@sssup.it

Abstract

In this work, we explore the relationship 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 all innovation activities, apart from process innovation and disembodied technical change, display a positive effect on high-growth performance. Also, 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.

Jelcodes:D21,O32

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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

1 Introduction

The relationship between innovation and firm performance has for long interested economists. The general intuition is obviously that innovation is among the key determinants of comparative advantages of firms 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 the 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 firm growth, focusing in particular on the linkages between innovative activities 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 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 relationship between sales growth and innovation, by looking at a wide set of innovation indicators that capture different sources, modes and output of innovative activity undertaken within firms. Extant empirical studies on the subject mostly focus on traditional proxies such as R&D and patents. On the contrary, exploiting a rich dataset on Spanish firms, we look at different measures of innovative input (distinguishing between internal vs. external R&D, investment in innovative machinery and equipment, purchase of licenses or know-how from other firms), at different output of innovation (process vs. product innovation), also distinguishing different types of product innovation (new-to-the-firm or new-to-the-market). 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 this study, however, is a limitation that we also 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 of 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, in turn failing to carefully 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, or high-growing, firms. Besides sharing the above-mentioned limitation of focusing only on patents or R&D, these studies apply basic quantile regression techniques. Exploiting the longitudinal dimension of our data, we can instead apply up-to-date quantile regression techniques designed to account for firm fixed effects. To the best of our knowledge, this is the first attempt in this direction within the growth-innovation literature.

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 and knowledge sources in successful generation of innovation output. We apply the same conceptual and methodological apparatus to ask whether different combinations of basic innovation activities (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 can 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. The other innovation activities tend to have a positive association with growth only in the top quartile of the growth distribution, that is for high-growth performance, although this is not the case with acquisition of disembodied knowledge and process innovation. 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 relationship and provides a potential explanation for the inconclusive results of previous studies which adopted a unidimensional approach.

The paper is structured as follows. In Section 2, we review the relevant literature, thus providing the background of our study. We describe our data and present the main variables in Section 3. Section 4 presents descriptive evidence on the innovation-growth relationship. Section 5 provides our main results, reporting standard panel estimates and Fixed-Effects quantile regressions. We next explore complementarities in Section 6, and finally conclude in Section 7.

2 Background framework

In this Section we discuss the relevant literature on the innovation-sales growth relationship, in turn motivating the gaps in the literature that we tackle in the present paper.[1]

Whilst theoretical models acknowledge the importance of innovation as a major driver of firm growth and success on the market (see Aghion and Howitt 1992; Aghion et al. 2005), the empirical literature does not fully support the theoretical expectations. There is a long series of studies that do find some positive effect of innovative activity, especially of R&D, on growth, from classical studies as Mansfield (1962) and Scherer (1965) or Mowery (1983). Interaction with other firms characteristics is then documented in Geroski and Machin (1992), who show that innovating firms grow faster, but only lasting until the firm loses proprietary control over the new knowledge employed, while Storey (1994) underlines the important role of initial size, with smaller firms achieving a more rapid growth after successful innovation.By contrast, there is also a considerable number of studies that do not find any significant effect of innovation on sales growth, like in Geroski et al. (1997), Geroski and Mazzucato (2002), Bottazzi et al. (2001) and Demirel and Mazzucato (2012).

The mixed empirical support for the existence of a strong link between innovation and sales growth might be related to the extreme complexity of the firms' innovative process. In turn, it has been shown that, since growth rates display fat-tailed distribution (Stanley et al., 1996; Bottazzi and Secchi, 2006; Coad, 2009), the process leading from innovative input to innovative output may show different effects according to the different positioning of a firm in the growth rates distribution, whereas more traditional regression studies are only informative about the "average firm". Already Freel (2000) shows that, although innovation does not necessarily determine firm growth, it may be relevant in boosting high-growth. And this is confirmed by a recent strand of literature that apply quantile regression techniques to disentangle the effect of

[1]There also exists a huge literature on the effects of innovation on growth of employment (see Vivarelli, 2014, for an exhaustive survey on the topic).

innovation proxies along the spectrum of the growth rates distribution (Coad and Rao, 2008; Hölzl, 2009; Falk, 2012; Colombelli et al., 2013). The common finding is indeed that innovation is actually relevant in the top quantiles, that is for hig-growth firms.

The literature still suffers from several limitations. In particular, studies on the subject tend to focus on traditional proxies of innovative activity such as R&D and patents. As recently emphasized in the extensive literature review in Audretsch et al. (2014), the great variety of innovation strategies undertaken by firms calls for a multidimensional approach to assess the actual contribution of innovation on corporate growth. In this paper, we exactly try to enlarge the picture on the role of different innovation activities or strategies in shaping firm growth on the market. The set of innovation indicators that we use are intended to capture different aspects of the innovative process. They cover the usual innovation input vs. innovation output dichotomy, but they also allow to investigate the role of internal vs. external sourcing of knowledge. The existing literature does not provide conclusive evidence on their effect on sales growth.

First, concerning the output side of innovation, many studies have highlighted 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 as the main outcome of the innovation process. Only few works have however considered the relationship 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 relationship between new processes and productivity (see Griffith et al. 2006; Hall et al. 2009; Mairesse and Robin 2009). 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 in new products represent the most important strategy for expansion and growth (Hay and Kamshad, 1994). But the evidence is mixed. Cucculelli and Ermini (2012) find that the mere introduction of products (dummy for product innovation) does not affect sales growth if one does not control for unobserved product characteristics, which the study tries to proxy through the tenure from last product introduction. And other studies confirm the importance of heterogeneity of new products, comparing the two measures of product innovation that we also use, that is the share of total turnover due to products-new-to-the-firm vs. products-new-to-the market (Hölzl, 2009; Corsino and Gabriele, 2011).

Second, moving to studies that explore the relationship between sales growth and innovation inputs, also in this case we observe a sort of resilience to abandon traditional measures such as expenses in in-house formal R&D. An exception is in the recent Segarra and Teruel (2014), showing that while internal R&D has a significant positive impact in the upper quantiles of the sales growth distribution, that is for high-growth, external R&D appears to be important only up to the median.

However, and third, despite rich data are available through innovation surveys about activities like outsourced R&D and acquisition of innovative technology, both embodied (investment in new machinery and equipment) and disembodied (acquisition of patents, know-how, licenses, etc.), we lack further attempts to exploit the distinction between internal and external sources of knowledge and innovation. despite. Theoretically, the acquisition of new knowledge or techniques or innovation from outside the boundaries of the firm has uncertain effects. On the one hand, it can improve the innovative capabilities of firms. But, on the other hand, exploitation of external sourcing is also subject to constraints due to absorptive capacity, complexity of user-producer interaction, and adaptation to specific characteristics and needs of each firm.

Overall, to our knowledge at least, Goedhuys and Veugelers (2012) provide the only attempt to reconstruct the relationship between sales growth and at least a subset of the various innovation strategies that firms have at their disposal. The paper exploits the logic of a standard augmented CDM model (Crepon et al., 1998) to recursively assess the relevance of internal vs. external R&D for product and process innovation, and to estimate the ensuing impact of successful new processes or products on stimulating sales growth.

We provide a different contribution. We look at a broader set of innovative indicators, encompassing internal vs. external R&D, process innovation, different types of product innovation, and embodied vs. disembodied technological acquisition, and then explore both their direct effects and the complementarities among them in sustaining sales growth.

3 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 as 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 small set of variables about firms' more structural and industrial characteristics, which essentially cover only annual turnover and total 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. Another advantage of the data is that there is no need to care about sample-selection issues. Contrary to other innovation surveys, both innovators and non-innovators fill in the entire PITEC survey.

Table 1: Composition of the panel

Time obs.	N. of firms	%	%Cum	N of 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.

We select our working dataset from an initial sample 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 transactions. 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 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 size 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 variables, 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 were 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 were 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.
6. *Embodied technological change* (intensity): Investment in innovative machinery and equipment, normalized by total turnover.
7. *Disembodied technological change* (intensity): Acquisition of external knowledge (patents, know-how, and other types of knowledge 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.

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%

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: Table reports basic descriptive statistics on the different innovation variables. Figures computed pooling over the working sample - 26,386 observations.

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 the sample report to 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.

4 Growth and innovation: descriptive evidence

As a first assessment of the relationship 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]

Table 3 shows basic descriptives of sales growth across the different subgroups. The subsamples are quite homogeneous in terms of number of observations, except for embodied and disembodied technical change, which are the two less frequently adopted activities in the data. Further, "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.

We next look at the unconditional distribution of sales growth rates, again across "innovators" and "non-innovators". Kernel densities (on log-scale) are reported in Figure 1. The estimates reveal differences between the two groups, with "non-innovators" generally more concentrated in the left part of the support. These asymmetries in the left tail are particularly pronounced for the two R&D indicators. The differences in the right tails are less clear-cut, with the two distributions substantially overlapping, irrespective of the innovation variable considered. This implies that "non-innovators" are nevertheless able to enjoy extreme positive growth events. The visual inspection is confirmed by a Fligner and Policello (1981) test of distributional equality (henceforth 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

[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.

Table 3: Descriptive statistics for sales growth by innovation status

		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 the working sample - 26,386 observations.

imply that "innovators" present a larger probability to experience superior growth performance than "non-innovators".

Overall, the observed distributional asymmetries suggest that the larger average growth observed within innovators can be due to innovators being 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 Growth and innovation: main results

In this section we present our main analysis. The empirical strategy is to separately investigate the relationship between sales growth and each innovation activity, conditional on a set of controls. We first look at the effect of innovation variables on average growth, through standard panel techniques, and then exploit fixed-effects quantile regressions to estimate asymmetries in the innovation-growth relationship 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

[3] Since one might argue that it takes time for innovation to be "translated" into sales growth, we also checked

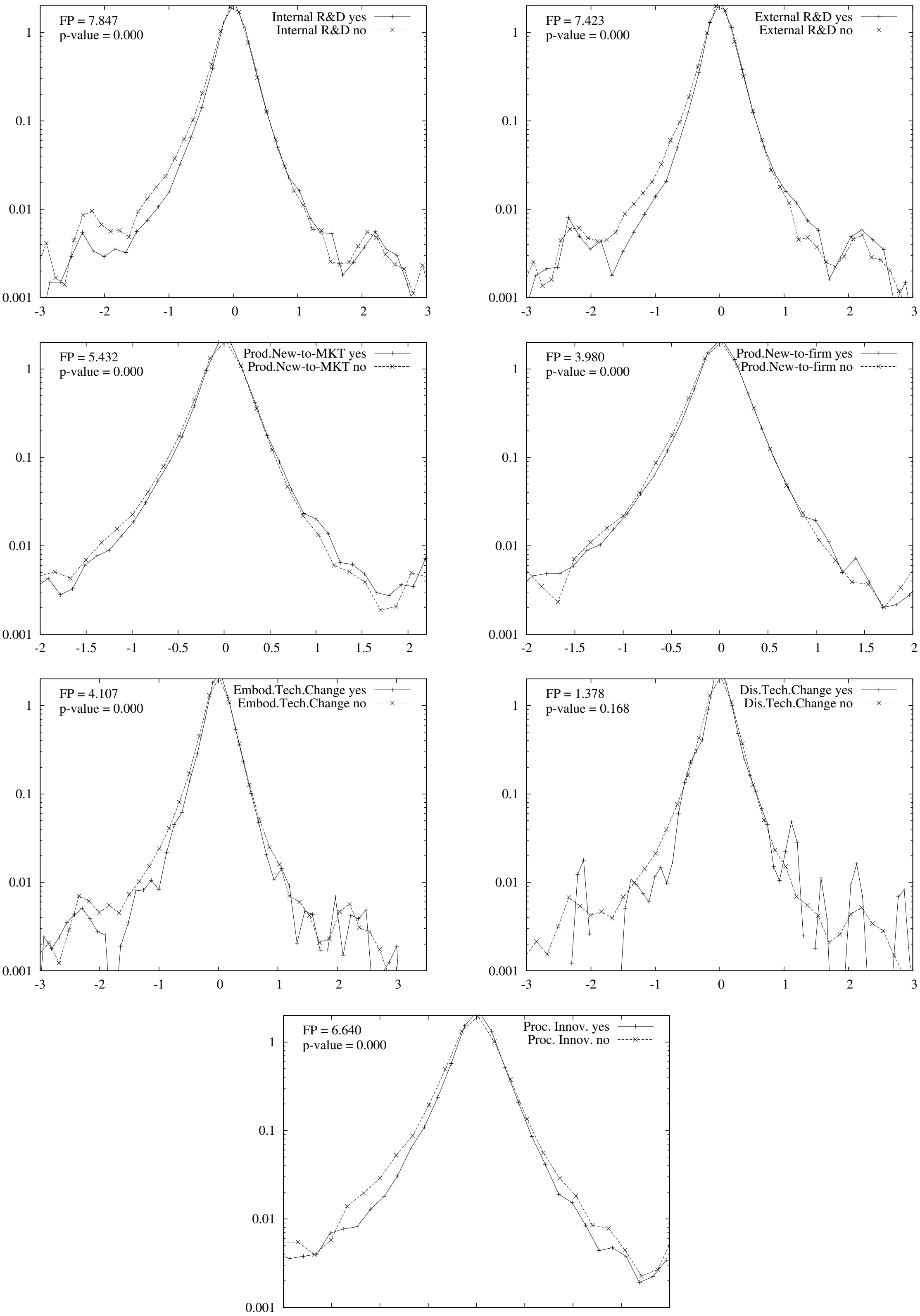

Figure 1: Kernel estimates (Epanenchnikov kernel) of sales growth rates densities for "innovators" vs. "non-innovators", defined as firms that do or do not engage in each innovation activity. Innovation proxies are Internal or External R&D (first row), Products new-to-the-firm or new-to-the-market (second 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 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 over the pooled sample used in regression analysis - 26,386 observations.

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] Table 4 reports the corresponding descriptive statistics. All the specifications also include a full set of industry (2-digit) and year dummies.

The coefficient of primer interest is of course α, capturing the effect of each specific innovation activity on sales growth. Inclusion of firm fixed-effects implies that the main parameter is identified through within-firm changes of the INNOV proxies over time. This helps mitigating 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 INNOV and other controls like age, size and export status. The same reasoning applies for other unmeasured factors jointly influencing growth and innovation, such as financial constraints, managerial and organizational characteristics, or input quality. Such an endogeneity issue is controlled for in standard panel GMM estimators, while up-to-date quantile regression techniques are not yet available to tackle this potential source of bias.

5.1 Panel estimates

We start presenting standard panel analysis of Equation (3), documenting the effect of the different innovation proxies on average sales growth. As a reference, we first show the results obtained with Fixed Effects-Within Estimator (FE), although this might be severely biased due to endogeneity and the presence of the lagged dependent variable. Secondly, we

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.

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.

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.[5] 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 selected, based on the usual Arellano-Bond tests for serial correlation and on Sargan/Hansen tests for overidentifying restrictions. We mainly comment on these results, since these are in principle more reliable.

In Table 5 we report the estimates of the models including the two measures of R&D intensity. The FE results reveal a positive and strongly significant relationship between sales growth and internal R&D intensity, whereas a barely significant (10% level only) association 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

[5]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. This is also confirmed by our results below.

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. Outsourced R&D does not support sales growth, possibly due to problems related to absorptive capacity or to coordination failures with the external provider of R&D services. Another explanation can be that firms tend to outsource more marginal R&D projects, i.e. those more loosely linked to the core activity or less relevant to product development, and thus less likely to impact on sales and market shares.

Concerning the control variables, the estimated coefficients display robust patterns, irrespective of the R&D 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 previous studies on Gibrat's law, where attempts to quantify growth rates autocorrelation provided 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 older and more mature firms. Fourth, we observe that export status as a negative and significant coefficient. This maybe unexpected, since the literature on micro-empirics of exports suggest that exporters typically reach superior performance than non-exporters. Recall however that a similar result is found on a different sample of Spanish firms in Hölzl (2009). 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 relationship 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 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 statistical significance in the model with 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 relationship with sales growth.

Table 7 presents the estimates concerning the other innovation proxies. In columns 1-2 we exploit 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 the role of process innovation on firm growth is mediated by productivity. Activities intended to change production processes and organizational settings tend to enhance firm efficiency, rather than to directly affect sales growth. We thus observe here the result of a lacking relationship between productivity and growth, recently suggested in several studies documenting that markets do not work as efficient

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.

selectors in redistributing market shares in favour of the more efficient firms (Bottazzi et al., 2008, 2010; Dosi et al., 2013).

A similar reasoning can also apply to explaining the estimated effect of embodied technical change (columns 3-4) through acquisition of new machineries. Indeed one can think that this specific activity has direct effects on productive efficiency or capacity utilization, while it can only indirectly impact on sales growth. And also in this case, we find no evidence of statistically significant effect in the GMM estimate.

In columns 5-6 we next find that also the proxy of disembodied technical change does not have a significant effect on subsequent growth. 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 sources (know how, patents, licenses) 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

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.

is at best indirect and in the end nil.[6]

Finally, we notice that in all the specifications of Table 7 the coefficient on the control variables are in accordance with the estimates described above for R&D and product innovation proxies.

5.2 Fixed-Effects quantile regressions

The distributional analysis provided in Section 4 recalls one of the major stylized fact of industrial dynamics, stating that firm growth rates are characterized by a fat-tail distribution. This means that standard regression techniques, by modeling the effects on the conditional expectation 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 exactly because one can uncover the asymmetries characterizing the innovation-growth relationship along the spectrum of the growth rates distribution. Existing studies, however, focusing only on R&D and patents and apply basic quantile regression methods. In this Section we exploit

[6]Also recall that only few firms engage in this activity, see Table 3 above.

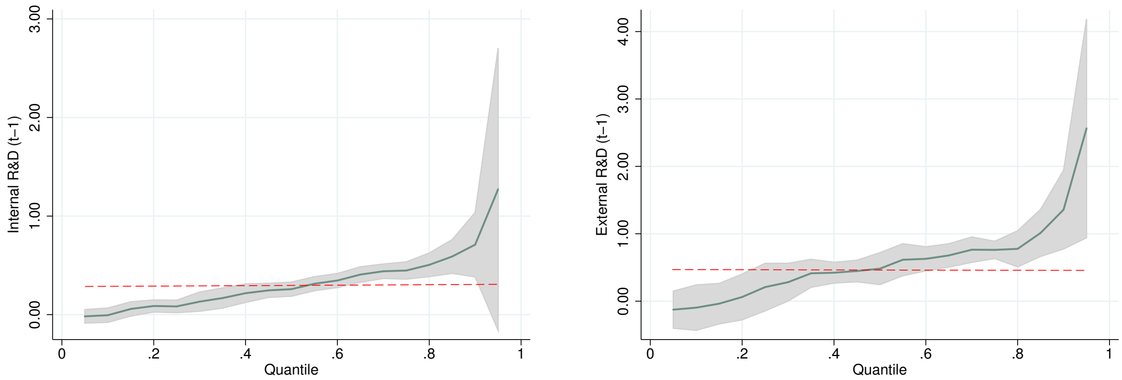

Figure 2: Fixed-Effects quantile regression estimates of coefficient α from Equation (3). Innovation proxies are Internal (left) and External (right) R&D intensity. The shaded areas represent 99% confidence band via bootstrapped standard errors. The horizontal line depicts FE estimates of α as benchmark.

the Fixed-Effects quantile regression estimator developed in Canay (2011), explicitly allowing for firm-specific unobserved heterogeneity.

Essentially, 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 a generic panel regression

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

where the dependent $Y_{i,t}$ is sales growth G as defined above, $X_{i,t}$ contains the set of explanatory variables (each innovation indicator INNOV, alternatively, plus the controls $\mathbf{Z}$), while u_i and $\epsilon_{i,t}$ are the firm-fixed effect and the standard disturbance term, respectively.

Next, the Canay (2011) estimator proceeds in two steps: (i) obtain an estimate of the individual fixed-effect through $\hat{u}_i = E_T[Y_{i,t} - X'_{i,t}\hat{\beta}]$, 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 $\hat{Y}_{i,t} = Y_{i,t} - \hat{u}_i$ and then obtain quantile regression coefficients through

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

which is just a quantile regression as in Koenker and Bassett (1978) on the transformed dependent variable.[7]

As we did with standard panel regression, we estimate our baseline Equation (3) separately for each innovation variable. In Figure 2, 3 and 4 we provide a graphical representation of the results focusing on the coefficient capturing the effect of the different innovation variables across the quantiles of the growth rates distribution.[8] To evaluate statistical significance, we also show a 99% confidence band, obtained from bootstrapped standard errors, as recommended in Koenker (2004) and Canay (2011). We also report an horizontal line indicating the FE coefficients estimated in the standard regression analysis.[9]

Figure 2 shows the results for the two measures of internal and external R&D. The quantile regression curves reveal clear heterogeneity in the effect of each indicator across the growth rates distribution. Two results are worth noticing here, common across the two proxies. First,

[7]The key assumption in the Canay estimator is that the fixed-effects are location shifters, meaning they affect all quantiles in the same way.

[8]Full set of coefficient estimates (innovation variables and controls) available upon request.

[9]It would be pointless to compare FE-quantile regressions with GMM estimates. Indeed, the main drawback of quantile regressions is that there is not yet a method addressing endogeneity, to our knowledge at least.

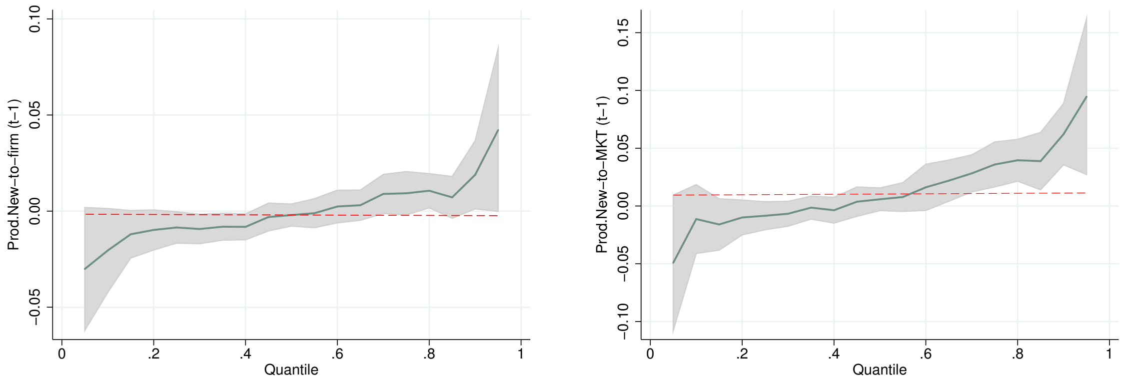

Figure 3: Fixed-Effects quantile regression estimates of coefficient α from Equation (3). Innovation proxies are % of sales due to products new-to-the-firm (left) and % of sales due to products new-to-the-market (right). Shaded areas represent 99% confidence band via bootstrapped standard errors. The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

for shrinking firms, that is in the bottom quartile, R&D expenditures have a weak or not statistically significant association with growth. Second, the coefficient estimates increase and become positive and significant in the central part (till the third quartile), and then are larger than the FE estimates in the top quartile. These asymmetries reveal that R&D provides a strong contribution to superior growth performance, i.e. for high-growth firms. The estimated coefficient on external R&D is twice as larger, but so is the standard error. The nil effect of R&D for firms belonging to the left tail is open to several interpretations. On the one hand, it may be that uncertainty of innovation often leads to unsuccessful outcomes, thereby making R&D efforts no more than a waste of resources. Our finding would imply that shrinking and non-growing firms are more often engaged in such unsuccessful dynamics. On the other hand, we can admit that R&D produces successful outcomes even for these firms, but the impact on sales is not strong enough to counteract a loss of market shares due to, for instance, a generally weak competitiveness of a firm in the market.

We comment on product innovation variables in Figure 3. For both variables the estimates resemble the patterns emerged for R&D. Indeed, there is no statistically significant association with growth until the top 20-15% of the growth rate distribution, but the estimates turn positive and significant in the top quantiles. This means that product innovation is relevant for high-growth. Noteworthy is the different magnitude of the estimated coefficients in the top quantiles: consistently with expectations, sales due to products new-to-the-market display a stronger association with total sales growth than sales due to products new-to-the-firm.

Next, in the top plots of Figure 4, we report the findings about Embodied and Disembodied technical change. Results for Embodied technical change mimic what we observe for the R&D variables. The estimates tend to be small or not even significant in the first quartile, and then become positive and significant starting from the median and through the upper quartile. Conversely, Disembodied technical change does not show any significant coefficient across the entire spectrum of the growth rates distribution.

The same result applies in the bottom plot of Figure 4, where we see that process innovation does not provide direct benefits in terms of sales growth. If anything, there might even be a mild negative effect among top-growing firms.

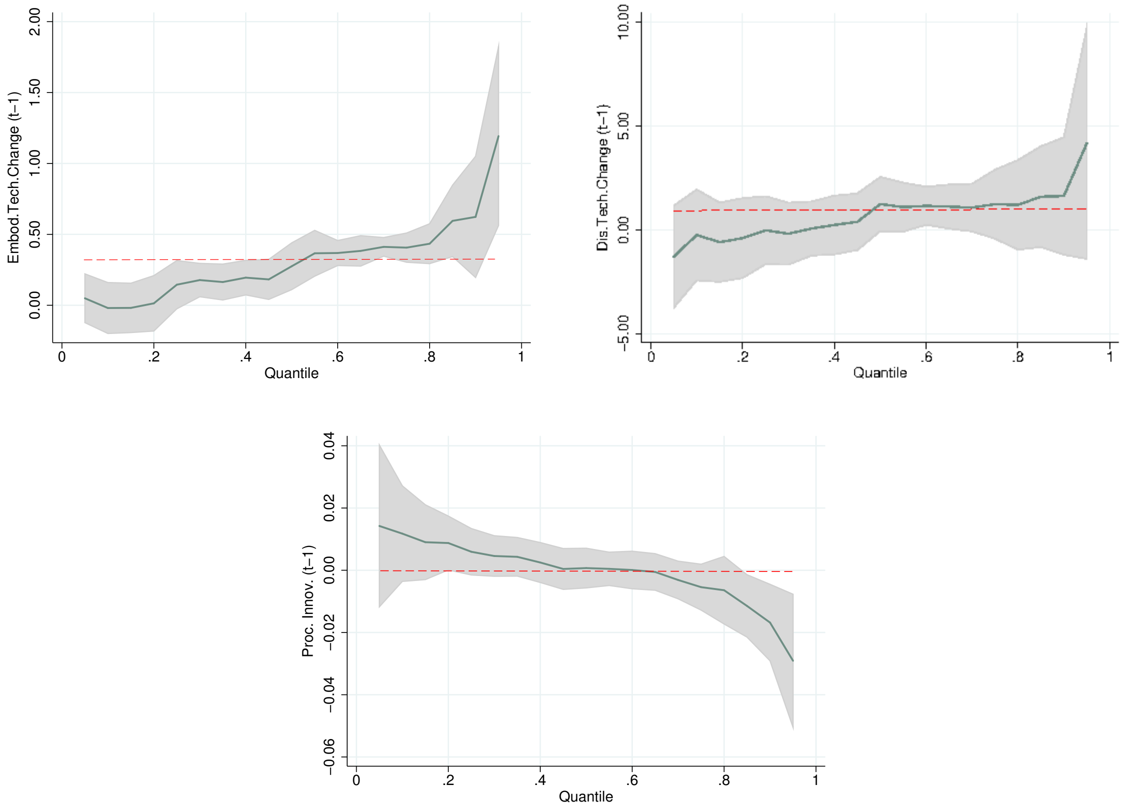

Figure 4: Fixed-Effects quantile regression estimates of coefficient α from Equation (3). Innovation proxies are Embodied (top-left) vs. Disembodied (top-right) technical change, and Process Innovation (bottom). Shaded areas represent 99% confidence band via bootstrapped standard errors. The horizontal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

6 Testing complementarity of innovation activities

In this Section we explore if sales growth originates from combinations of different innovation activities, rather than from each single one. Indeed, firms in reality often pursue different innovation strategies, undertaking different innovation activities at the same time. The outcome of innovation in terms of sales growth can be different depending on the complexity of the strategy pursued, in terms of the number and the type of activities performed at the same time. Each different combination may entail specific costs and challenging coordination issues, and thus hamper growth, while also increasing the ability to create and capture growth opportunities.

The 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 supermodular in X_j and X_i, that is

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

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 but X_i is not chosen. This approach to complementarity has been adopted by a number of studies exploring complementarity of different innovation inputs, or of obstacles to innovation, in generating innovation outputs (see, e.g., Mohnen and Roller, 2005; Catozzella and Vivarelli, 2014). We apply the same framework to explore super-modularity of the growth function with

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

respect to innovation activities.

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

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

Notice that these are mutually exclusive categories. Of course, firms may engage in none, just one or more of these activities at the same time. We build all the possible combinations among these four categories, ending up with a total of $2^4 = 16$ possible "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 engage 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 G is sales growth, $\mathbf{Z}$ is the usual set of lagged controls as in the main Equation (3), and we normalize S_{0000} to zero. Notice that the strategy dummies are measured in $t-1$ and change over time.

The definition of super-modularity of G with respect to the lattice S is rewritten as

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

The number of non trivial inequalities implied by the 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 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 rewritten as follows:

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 $\gamma = (b_{0001}, b_{0010}, ..., b_{1111})'$ 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

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

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 D lies between the two bounds.

The main requirement for the procedure to work is that $\hat{\gamma}$ is a consistent estimate of γ. We estimate the growth function via the GMM-DIFF estimator. This allow, 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 set 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 report the estimated D statistic for the different pairwise combinations of the basic innovation activities. Cases where the null of complementarity cannot be rejected are in bold (at the 10% level, which seems standard in previous studies).

Results support complementarity only in two cases. First, we find that there is complementarity between INT and NEWP, meaning that these two activities are more important for

Table 9: Estimation results & complementarity test

	Estimation	Complementarity test	
Dep.Var. is G_t	(1)	Pair	Wald statistic
$\text{STR}_{1,t-1}$	0.0293	INT-EXT	5.3215
	(0.063)	INT-NEW	**1.6045**
$\text{STR}_{2,t-1}$	0.0769	INT-PRO	4.8413
	(0.147)	EXT-NEW	3.0288
$\text{STR}_{3,t-1}$	0.1986	EXT-PRO	6.0155
	(0.155)	NEW-PRO	**1.6156**
$\text{STR}_{4,t-1}$	0.4623**		
	(0.208)		
$\text{STR}_{5,t-1}$	0.0309		
	(0.080)		
$\text{STR}_{6,t-1}$	-0.1448		
	(0.454)		
$\text{STR}_{7,t-1}$	0.1330		
	(0.140)		
$\text{STR}_{8,t-1}$	0.1798**		
	(0.090)		
$\text{STR}_{9,t-1}$	0.0300		
	(0.102)		
$\text{STR}_{10,t-1}$	0.1849*		
	(0.105)		
$\text{STR}_{11,t-1}$	0.1464		
	(0.114)		
$\text{STR}_{12,t-1}$	0.0886		
	(0.123)		
$\text{STR}_{13,t-1}$	0.1888**		
	(0.095)		
$\text{STR}_{14,t-1}$	0.2091		
	(0.129)		
$\text{STR}_{15,t-1}$	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).

growth when done together, than when they are carried out separately. We therefore confirm the crucial role of internal R&D, but we can add that internal R&D pays even more in terms of growth when it is carried out together with product innovation. At the same time, we recover here a role for product innovation, suggesting that introduction of new products is more likely to impact on growth when formal R&D activities are 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 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 it has an effect in combination with the capacity to introduce new products. The result indeed indicates that restructuring of production processes are effective only if related to a simultaneous change in new products.

Conversely, process innovation is not complement with the other innovation activities, confirming the overall weak role of such variable in fostering sales growth. And, finally, we do not detect any complementarity of external sourcing of knowledge with none of the other innovation activities. The finding recalls an already mentioned explanation hinting at difficulties in integrating knowledge and technologies produced outside the firm, due, e.g., to coordination with external "providers" or to weak absorptive capacity. These difficulties were already emerging in the above analysis of the separate effect of external R&D, embodied and disembodied technical change.

7 Conclusions

The relationship between innovation and firm growth is a classical, yet still puzzling topic. While theory tends to predict a strong positive link, the empirical literature provides mixed results. Moreover, most studies tend to focus on the effect of innovation on productivity and employment growth, perhaps given the important implications for economic growth, job creation and job destruction. We also face 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 evidence on the relationships between success on the market, in terms of sales growth, and a rich 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, findings from standard panel regression analysis, controlling for firm fixed-effects and endogeneity, deliver a negative result. The (causal) effect of innovation is, in general, quite modest. Once controlling for endogeneity, only investing in R&D carried out internally stands out as a robust driver of subsequent sales growth. Conversely, we are not able to find any significant effect of external R&D, process innovation, increases in the sales due to new products, as well as of acquisition of embodied or disembodied new technologies.

This negative result is striking, at first, as one generally thinks that innovation spurs growth. However, this set of findings confirm previous studies that highlight how the effect of innovation activities on average growth may be difficult to detect. And there are explanations for some of the findings. The lacking correlation between activities that involve external sourcing of new knowledge or new technologies (external R&D, 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.

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. Identification trough within-firm changes implies that our negative results is driven 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, mutatis mutandis, can be extended to the other innovation variables for which we do not find significant results. This explanation, however, can have some relevance only in the case of the dummy indicator of process innovation. That variable is indeed fairly persistent, since "innovators" and "non-innovators" tend to remain like that over the sample period. 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 variation within firms. 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.

The second piece of evidence that we provide is that we recover a positive effect for most of the innovation variables when we look at their association with growth along the entire spectrum of the growth rates distribution. Estimates of quantile regression controlling for firm fixed-effects show that all variables, with the exception of process innovation and disembodied technical change, have a positive and significant coefficient in the upper quartile, that is for high-growth episodes. In this respect, our analysis supports the view that many innovation activities are beneficial, but only for high-growth firms. Notice that 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.

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 recover a role for both product and process innovation. Indeed, we find that the beneficial effect of internal R&D is stronger when coupled with product innovation, and that process and product innovation have a stronger association with growth if carried out together.

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