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

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September 14, 2014

Abstract

The relationship between innovation and firm growth is a classical, yet still puzzling topic. While theory predicts a strong positive link, the empirical literature provides mixed results. In this work, we account for the multifaceted nature of the innovation activities engaged by firms, exploring the relationship of sales growth with a wide set of innovation indicators that capture the different sources, modes and results of the innovative activity undertaken within firms. By taking advantage of a rich panel on innovation activity of Spanish manufacturing firms, reporting detailed CIS-type information continuously over the period 2004-2011, we combine standard panel estimates of the average effect of innovation strategies with newly developed fixed-effects quantile regressions allowing to unravel asymmetries in the innovation-growth relationship. We find that R&D (especially internal), acquisition of innovative machinery and equipment and, to a smaller extent, product innovation (especially for products new to the market), display a positive association with subsequent sales growth, both on average and even more strongly for high-growth firms at the top quantiles of the growth rates distribution. Conversely, we do not detect any statistically significant effect for process innovation and disembodied technical change.

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

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1 Introduction

The relationship between innovation and firm performance has for long interested economists. The general intuition is obviously that innovation is the key to determine the 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 both 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 growth and innovation, by looking at a wide set of innovation variables that capture the different sources, modes and types of innovative activity undertaken within firms. Extant empirical studies on growth and innovation 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 modes of innovation (process vs product innovation), at different types of product innovation (new to the firm or new to the market, in turn proxing for more imitative vs more innovative efforts). 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 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, 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 included 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; 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 the 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.

The paper is structured as follows. After a brief review of the related literature (Section 2), we describe our data in Section 3. Section 4 and Section 5 provide the empirical framework, the methods adopted in the analysis, and the main results of our work. Section 6 concludes.

2 Related literature

The conspicuous literature on firm growth has provided robust evidence about the highly stochastic nature of this process, where a relevant role is played by the unobserved firm-specific characteristics. Notwithstanding, a notable number of contributions have found that growth is strongly influenced by the firm or entrepreneur's specificities. Among these factors, firm innovative activity is among the most investigated. However, the relationship between firm growth and innovation still represents a puzzling topic. Whilst theoretical models that relate these two dimensions of company dynamics acknowledge the importance of innovation as a major driver of firm growth (see Aghion and Howitt 1992; Aghion et al. 2005), the empirical literature provides mixed evidence and does not fully support the theoretical expectations. In this Section we briefly discuss some of the most relevant contributions in the field, in turn motivating the gaps in the literature that we tackle in the present paper. We devote more attention to studies investigating sales growth, which are more directly related to our analysis.[1]

There is a long series of studies that do find some positive effect of innovative activity, especially of R&D, on growth. The early papers documenting this fact go back to the 60s. Mansfield (1962) carries out a detailed assessment of the steel and petroleum sectors by using a long time series and finds that successful innovators grow faster. Similar results are also found in Scherer (1965), analyzing the patenting activity of the 365 largest US companies, and in Mowery (1983), looking at the effect of R&D employment on the growth of US manufacturing industries over a 25-years period. In their influential paper, Geroski and Machin (1992) concentrate on 539 quoted UK firms that introduced at least a major innovation, observed over more than ten years. They find that innovating firms are more profitable and grow faster, but the increase in sales is transitory, lasting only until the firm loses proprietary control over the new knowledge employed. Storey (1994) corroborates this finding and underlines the important magnifying role played by the initial size, with smaller firms achieving a more rapid growth after having been successful in innovating. Stam and Wennberg (2009) explicitly target new start-ups and show that the effects of R&D on new products development and hence on growth is present only in high-tech sectors.

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) and Geroski and Mazzucato (2002). The contribution in Bottazzi et al. (2001) is particularly relevant for the unusually detailed level of analysis (product-level). They target the top-150 world pharmaceutical firms, and conclude that the innovative position of a firm (measured either by the discovery of new chemical entities or by the share of patented products) is not associated with growth of sales.

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, a robust stylised fact emerging from industrial economics is that the firm growth rates distributions are characterised by wide heterogeneity and a tent shape (see Stanley et al., 1996; Bottazzi and Secchi, 2006; Coad, 2009), whatever the level of sectoral aggregation considered (Dosi, 2007). In this respect, for its inherent nature, 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

[1]There also exists a huge literature on the effects of innovation on growth of employment, where the main focus is on the labour-saving vs labour augmenting role of innovation, and topics related to skill-bias technical change (see Vivarelli (2014) for an exhaustive survey on the topic). We do not discuss this literature here, as we are more interested in a measure of growth capturing success on the market.

distribution. Already Freel (2000), on a sample of 228 small UK manufacturing disaggregated by differential innovativeness, and show that, although innovation does not necessarily determine firm growth, it may be relevant in boosting high-growth. More recently, a growing literature exploits quantile regression techniques to disentangle the effect of innovation proxies across the spectrum of the distribution of growth rates, whereas more traditional regression analysis simply is only informative about the "average firm". Coad and Rao (2008) work with firms active in four sectors with fast changing technologies, and find that innovation, measured in terms of R&D and patents, has an asymmetric impact over the sales growth distribution, with high-growth firms deriving the greatest benefits from their innovative efforts. The approach is also popular within studies looking at those companies labeled as high-growth firms or or 'gazelles'. For instance, Hölzl (2009) analyses CIS-III data for 16 countries, and shows that R&D is much more important for high-growth SMEs in countries that are closer to the technological frontier, arguing that such firms derive much of their drive from the exploitation of comparative advantages.

This methodological approach has allowed to, at least partially, reconcile the empirical evidence with the theoretical expectation of a strong influence of innovation on firm growth. Despite these important methodological advancement, however, the literature is still underdeveloped. In particular, studies on the subject are still focusing on traditional proxies such as R&D and patents. Yet, as recently emphasized in the extensive literature review in Audretsch et al. (2014), the high level of complexity of R&D and the the great variety of innovation strategies undertaken by firms, call for a multidimensional approach to assess the actual contribution of different innovation activities on corporate growth. In this paper we exactly seek to provide a wider picture, exploring the evidence on the role of different innovation strategies and activities in shaping firm growth on the market.

On the output side of innovation, it is widely recognized that patents are not the only measurable outcome of the innovation process. Many innovation surveys now allow to look at direct proxies for product and process innovations as well (see Griffith et al. 2006; Parisi et al. 2006; Hall et al. 2008, 2009). Concerning product innovation, it is quite plausible to expect a positive link between new products and sales growth, as indeed investment in new products represents the most important strategy for expansion and growth (Hay and Kamshad, 1994). Only few works have however considered the relationship between sales growth and proxies of innovative output alternative to patent. The above mentioned contribution by Hölzl (2009) provides evidence on the effect of two quantitative innovative output measures, namely the share of total turnover stemming from innovative products that are new for the firm or new for the market. The results show that the latter measure, somewhat capturing more important or more radical innovation, is of great importance for high-growth firms, in particular for those located in countries closer to the technological frontier. Corsino and Gabriele (2011), in a sample of worldwide high-tech firms, find conversely that more incremental product innovations introduced in the recent past positively affect sales growth.

On the other hand, studies that do consider the role of process innovation on firm performance almost exclusively look at the relationship with productivity. Indeed, while there is a convincing evidence that new processes, restructuring and recombining foster productivity (see Griffith et al. 2006; Hall et al. 2009; Mairesse and Robin 2009), there is practically no evidence about the direct impact of process innovation in boosting sales growth. To the best of our knowledge, a notable exception is in the recent Goedhuys and Veugelers (2012), on the growth determinants of a sample of Brazilian manufacturing firms. The results show that process innovation has no effect on sales growth. The suggested interpretation is that more cost efficient production may show its beneficial effects on sales in a later stage after an initial period of restructuring, having instead a more immediate influence on other dimensions of firm performance such as productivity.

Moving to studies that explore the relationship between sales growth and innovative input side, 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 represented by the recent work of Segarra and Teruel (2014). Although their main goal is to analyze the impact of R&D on firm growth, they also provide evidence that while formalized R&D shows a significant positive impact in the upper quantiles of the sales growth distribution, external R&D appears to be important only up to the median. We lack attempts to widen the scope of research to the impact on growth of activities like outsourced R&D and technological acquisition, both embodied (investment in new machinery and equipment) disembodied (acquisition of patents, know-how), for which quite rich dataset are now available. This is quite unfortunate, given the central role that innovation scholars suggest these activities play in determining innovation success of firms. Santamara et al. (2009), for example, show that non-R&D activities are crucial factors for innovation outputs (both product and process innovation). Pellegrino et al. (2012) and Conte and Vivarelli (2014) provide evidence about the relevant role played by embodied technological change in fostering firm innovative success, in terms of total turnover stemming from sales of new or significantly improved products, especially in low-tech industries, and for small and young firms.

Overall, the literature lacks an attempt to systematically correlate sales growth with the large variety of innovation activities or strategies that firms have at their disposal. To the best of our knowledge, the only notable exception is the already mentioned Goedhuys and Veugelers (2012), on the growth determinants of a sample of Brazilian manufacturing firms. The authors employ a recursive model allowing to simultaneously assess the relevance of internal vs. external R&D for product and process innovation, and the ensuing impact that successful new processes or products have in stimulating growth. We provide a different contribution, by taking a fresh look at the direct relationship between sales growth and a broader set of innovative indicators encompassing internal vs. external R&D, process innovation, types of product innovation, and embodied vs. disembodied technological acquisition.

3 Data and descriptive analysis

In this section we present the sample and our main variables, and provide preliminary analysis on the relationship between sales growth and the different innovation variables.

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, together with general information about the firm (main industry of affiliation, turnover, employment, founding year, industrial group), PITEC also includes a (much larger) set of innovation 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 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 relationship between

Table 1: Composition of the panel

Time obs.	N. of firms	%	%Cum	N of obs.
1	140	2.76	2.76	140
2	230	4.54	7.31	460
3	250	4.94	12.24	750
4	328	6.48	18.72	1,312
5	972	19.19	37.91	4,860
6	3,144	62.09	100	18,864
Total	5,064	100		26,386

Note: the final sample only includes firms for which two lags of the dependent variables are available. This implies that t=1 refers to firms that are observed for at least three periods, t=2 corresponds to firms that are observed for four periods and so on.

innovation variables and patterns of sales growth. 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.

We select our working dataset from an initial sample of 100,016 firm-year observations over the period 2004-2011. First, we focus on manufacturing firms, discarding all firms operating in the primary (1,628 observations), construction (3,914 observations), utilities (720 observations), sewage/refuse disposal (318 observations) and services sectors (42,919 observation). Second, we look at organic growth, hence we discard all firms involved in M&A transactions (4,658 observations). The resulting sample of 45,859 firm-year observations is further reduced by excluding all the missing values (19,473 observations) for the variables used in our empirical exercise (see below).

Table 1 depicts the composition of the final sample, consisting of 26,386 firm-year observations. The panel is unbalanced but the large majority of firms (around 62%) are observed over the entire time window, whereas another 20% persists in the data for 7 periods, and only a negligible percentage (7,31%) for less than 5 periods.

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. In this way 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 offer a multidimensional view about innovation strategies, we employ the following 9 indicators of innovative activity, available for each firm in each year:

1. Total R&D (intensity): Total R&D expenditures, normalized by total turnover.
2. External R&D (intensity): Extramural R&D expenditures, normalized by total turnover.
3. Internal R&D (intensity): Intramural R&D expenditures, normalized by total turnover.
4. Product Innovation: Binary indicator equal to 1 if the firm introduces new or significantly improved products, and zero otherwise.
5. Product Innovation 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.
6. Product Innovation 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.
7. Process Innovation: Binary indicator equal to 1 if the firm introduces new or significantly improved processes.
8. Embodied technological change (intensity): Investment in innovative machinery and equipment, normalized by total turnover.
9. 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.

Most of these proxies from PITEC maps with their usual 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

Table 2: Innovation variables - Descriptives

	Mean	SD	Median	Min	Max
R&D$_{t-1}$	0.037	0.193	0.006	0	9.316
Internal R&D$_{t-1}$	0.031	0.161	0.004	0	7.986
External R&D$_{t-1}$	0.006	0.055	0	0	3.353
Prod. Innov$_{t-1}$	0.633	0.482	1	0	1
Prod. New-to-MKT$_{t-1}$	0.099	0.225	0	0	1
Prod. New-to-firm$_{t-1}$	0.248	0.352	0.056	0	1
Proc. Innov$_{t-1}$	0.633	0.482	1	0	1
Emb.Tech.Change$_{t-1}$	0.006	0.047	0	0	3.441
Disemb.Tech.Change$_{t-1}$	0.000	0.005	0	0	0.555

Notes: Table reports basic descriptive statistics on the different innovation variables. Figures over the pooled sample used in regression analysis - 26,386 observations.

turnover instead of absolute figures. The binary categorization between product innovators and non-product innovators is also quite standard. The two variables built from sales related to products new-to-the-firm or new-to-the market, although correlated, are usually interpreted as proxies for two distinct modes of product innovation. The introduction of products perceived as new-to-the-market connects with the ability to perform "true" or "more radical" innovation, resulting in more valuable products. Conversely, introduction of products new only to the firm is usually considered as a proxy of more incremental and mainly imitation-based innovation. The dummy for process innovation has the standard interpretation as capturing reorganization of production or implementation of new processes. We also follow the common practice to interpret acquisition of new machineries and of external knowledge as two proxies for two alternative modes of external sourcing of knowledge, respectively capturing embodied and disembodied technical change.

Table 2 reports descriptive statistics for the 9 innovation indicators. Firms in our sample appear more prone to undertake internal generation of knowledge rather than searching for external sources of innovation. Indeed, on average, 3.1% of the firms' turnover is invested in intramural formalized R&D, while this percentage decreases to 0.6% for extramural R&D and acquisition of innovative machineries and equipment, and it is close to 0 in the case of investment in disembodied technological change. Furthermore, all the indicators display highly skewed distributions, suggesting considerable heterogeneity in the innovative behavior. From the indicators of innovative

Table 3: Firm growth and innovation status - Descriptives

	Growth descriptives				
	Mean	Median	Min	Max	Obs
Total R&D No	-0.044	-0.018	-4.813	3.853	10,250
Total R&D Yes	0.008	0.006	-3.821	4.674	16,136
Internal R&D No	-0.040	-0.016	-4.813	3.853	11,225
Internal R&D 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
External R&D Yes	0.022	0.012	-3.821	4.674	7,387
Prod. Innov. No	-0.027	-0.012	-4.813	4.674	10,235
Prod. Innov. Yes	-0.002	0.002	-3.958	3.57	16,151
Prod.New-to-firm No	-0.021	-0.007	-4.813	4.674	17,200
Prod.New-to-firm 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
Prod.New-to-MKT Yes	-0.002	0.002	-3.958	3.57	16,149
Proc. Innov. No	-0.032	-0.016	-4.813	4.674	10,290
Proc. Innov. 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
Embod.Tech.Change 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
Dis.Tech.Change Yes	0.016	0.001	-2.759	2.615	560

Notes: Table reports basic descriptive statistics on G_t by splitting the sample into "Innovators" vs. "Non-innovators" according to the different proxies of innovative activity. Figures over the pooled sample used in regression analysis - 26,386 observations.

output, we see that firms are equally oriented towards products and process innovation, as indeed around 63% of the sample performs both. On the other hand, the share in total sales due to products new-to-the-market is on average smaller than the share of sales from products new only to the firms (9.9% *vs* 24.8%). This connects with the intuition that truly innovative products are more difficult to achieve and more rare than imitative products.

3.3 Preliminary evidence

To provide a preliminary picture of the relationship between sales growth and innovation, we compare the growth rates distributions across innovators and non-innovators along each innovation variable, that is splitting the sam-

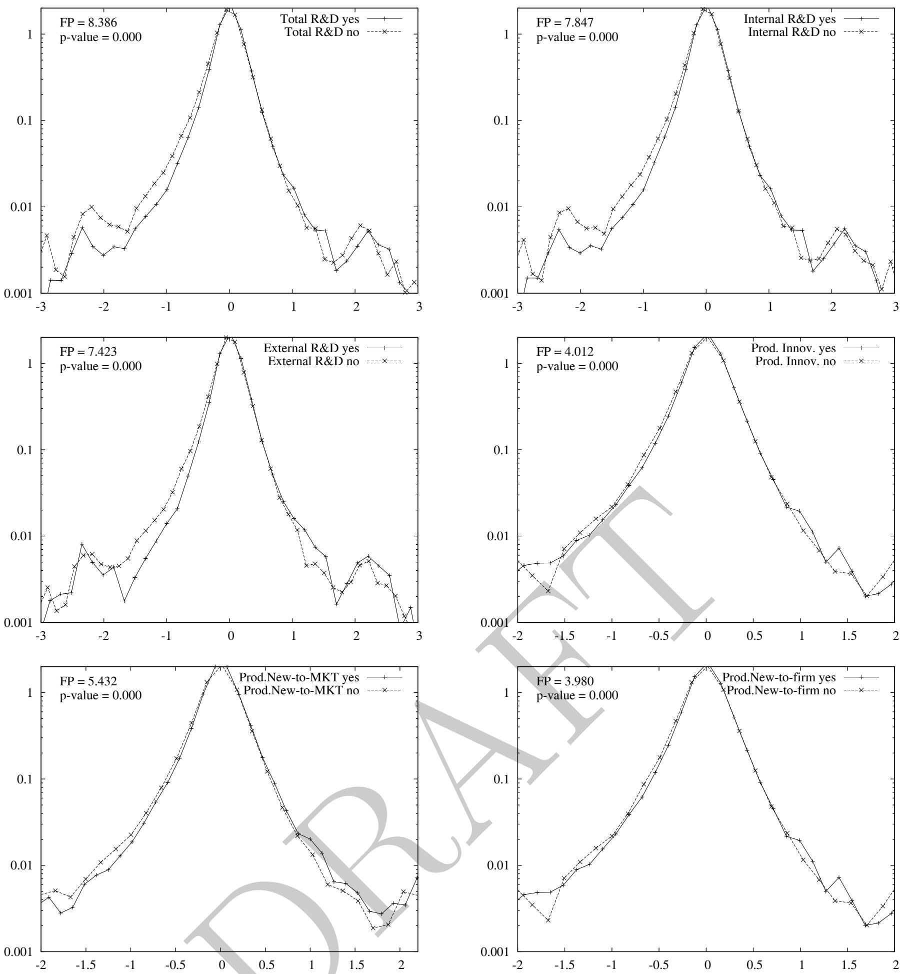

Figure 1: Kernel estimates of sales growth rates densities by innovation proxy: Total, Internal and External R&D; and Product innovation, also distinguishing between products new-to-the-firm or new-to-the-market. Figures also report Fligner and Policello (1981) test of stochastic dominance for comparison between "innovators" and "non-innovators", defined as firms that do or do not engage in each innovation activity. Positive and significant FP statistic indicates that innovators dominate non-innovators along the innovation proxy considered.

ple between firms that do or do not undertake a specific innovative activity.[2]

Table 3 reports basic descriptive statistics across different subgroups. The

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

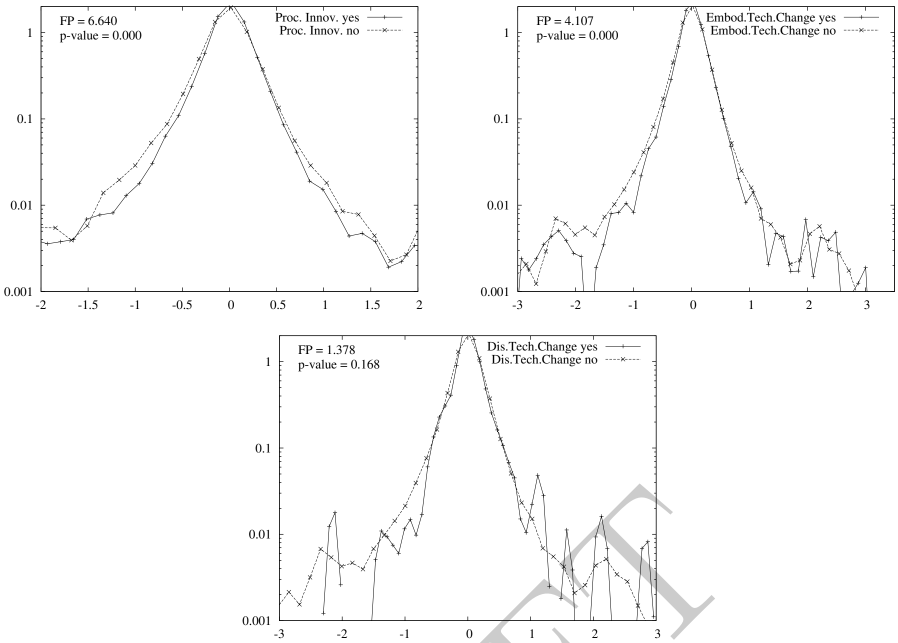

Figure 2: Kernel estimates of sales growth rates densities by innovation proxy: Process Innovation, and Embodied vs. Disembodied technical change. Figures also report Fligner and Policello (1981) test of stochastic dominance for comparison between "innovators" and "non-innovators", defined as firms that do or do not engage in each innovation activity. Positive and significant FP statistics indicates that innovators stochastically dominate non-innovators along the innovation proxy considered.

subsamples are quite homogeneous in terms of size, except for embodied and disembodied technical change, which clearly represent the least frequently adopted strategies. 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-innovator.

In Figure 1 and Figure 2 we look at the entire growth rate distribution across innovators and non-innovators. We report kernel estimates of the growth rates densities, and we carry out a non-parametric test of stochastic equality based on Fligner and Policello (1981) test (henceforth FP), allowing to assess which of the two distributions stochastically dominates the other along each innovation variable considered.[3] The estimates (on log-scale) re-

[3]The FP test is robust to non-normality, and to unequal variance and numerosity of

veal differences between the two groups, with non-innovative firms generally more concentrated in the left part of the support. These asymmetries in the left tail are particularly pronounced if one takes R&D indicators (total, internal or external). The differences in the right tails are less clear-cut, with the two distributions substantially overlapping, irrespective of the innovation indicator considered. This implies that non-innovative firms are nevertheless able to enjoy extreme positive growth events. The visual inspection is then confirmed by looking at the FP statistics. The null hypothesis of stochastic equality is always rejected (except for technological acquisition) and the positive FP statistics imply that innovators present an higher probability to experience superior growth performance than their non-innovative counterparts.

Overall, the evidence points at a positive association between sales growth and innovation, although this might be due to innovators being more able to avoid below-average growth rates, than to their superior capacity to support above average and faster growth.

4 Regression analysis

We next move to regression analysis. Our empirical strategy is to separately investigate the relationship between sales growth and each innovation activity. The baseline regression equation reads:

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

where $INNOV$ stands alternatively for each of the 9 innovation variables, while $\mathbf{X}$ is a set of control variables. Both INNOV and the controls enter with a 1-year lag, at least partially controlling for potential simultaneity.[4] Controls include the lagged dependent variable ($G_{i,t-1}$), 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.[5] Table 4 reports the corresponding descriptive

the two compared samples.

[4]Since one might argue that it takes time for innovation to be "translated" into sales growth, we also checked models allowing for longer lag distance between innovation regressors and growth. The findings are consistent with the results from our baseline 1-year lag specification.

[5]The $PubFund$ dummy records any kind of public financial support for innovation activities from Spanish local or government authorities and from the EU bodies, includ-

Table 4: Descriptive statistics for the control variables

	Mean	SD	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.

statistics. All the specifications also include a full set of industry and year dummies.

The coefficient of primer interest is α, capturing correlation between growth performance and each specific innovation activity. We report basic pooled OLS (POLS), for reference, identifying α through the variation of each $INNOV$ proxy across firms, and standard Fixed Effects (FE) estimates with firm fixed effects, thus identifying the main parameter through within-firm changes of the $INNOV$ 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 direct measures of productivity: firm fixed effects absorb at least the time-invariant component of efficiency, while the time varying component is possibly interacting with other controls like age, size and export status. A similar reasoning applies for other potential factors jointly influencing growth and innovation. We highlight at this stage that we cannot give any causal interpretation to the estimates of α.

In Table 5 we show results obtained with the three measures of R&D intensity. The POLS estimates tend to reveal a positive and strongly significant relationship with Total R&D intensity. When we split R&D activity into intra vs. extra-mural research activity, however, we observe a statistically significant, and positive coefficient only for Internal R&D. Estimates with firm fixed effects corroborate the results: total R&D and internal R&D

ing 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: Regression analysis - R&D intensity

Dep.Var. is G_t	Innovation Proxy					
	Total R&D		External R&D		Internal R&D	
	POLS	FE	POLS	FE	POLS	FE
	(1)	(2)	(3)	(4)	(5)	(6)
INNOV_{t-1}	0.147***	0.207***	0.234	0.491*	0.184***	0.216***
	(0.042)	(0.076)	(0.151)	(0.289)	(0.045)	(0.078)
G_{t-1}	-0.185***	-0.308***	-0.186***	-0.312***	-0.186***	-0.309***
	(0.015)	(0.013)	(0.015)	(0.012)	(0.015)	(0.013)
$\ln Empl_{t-1}$	0.007***	-0.160***	0.005**	-0.162***	0.007***	-0.161***
	(0.002)	(0.022)	(0.002)	(0.022)	(0.002)	(0.022)
$\ln Age_t$	-0.019***	-0.168***	-0.022***	-0.195***	-0.018***	-0.172***
	(0.004)	(0.053)	(0.004)	(0.055)	(0.004)	(0.053)
$Export_{t-1}$	0.026***	0.003	0.026***	0.003	0.025***	0.004
	(0.006)	(0.015)	(0.006)	(0.015)	(0.006)	(0.015)
$PubFund_{t-1}$	0.022***	0.001	0.029***	0.003	0.022***	0.001
	(0.005)	(0.007)	(0.005)	(0.007)	(0.005)	(0.007)
$Group_{t-1}$	0.003	-0.021	0.004	-0.020	0.003	-0.021
	(0.005)	(0.020)	(0.005)	(0.020)	(0.005)	(0.020)
Obs	26,386	26,386	26,386	26,386	26,386	26,386
Industry dummies	yes	yes	yes	yes	yes	yes
Year dummies	yes	yes	yes	yes	yes	yes

Notes: Estimates of Equation 3. Pooled OLS (POLS) and Fixed-Effects (FE) Robust standard errors in parenthesis. ***: significant at the 1% level; **: significant at the 5% level; *: significant at the 10% level.

remains strongly significant, with positive sign, while external R&D intensity is significant but only at very low confidence level (10%). The point estimates across the two estimation methods differ in magnitude, but cannot be considered as statistically different within 1-standard error confidence band.

The estimated coefficients on control variables display robust patterns, irrespective of the innovation proxy considered. First, we find negative autocorrelation of sales growth, although the estimated coefficient might be biased by standard endogeneity of the lagged dependent variable. Second, lagged size (in terms of employment) has a positive and significant, although small (about 0.005) coefficient in the POLS model, while more reliable FE estimates reveal a steady negative and strongly significant association with size, with an elasticity of about -0.160. The result is in line with the expectation that, on average, small firms tend to grow more, and recall the literature about violations of Gibrat's Law predicting no correlation between average growth and average size. The sharp difference in estimated coefficients across POLS and FE is in line with the expected upward bias of POLS estimates, due to uncontrolled factors such as productivity, which are likely to positively correlate with both growth and size. Third, age is also 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. Also in this case the observed strong upward bias of POLS estimates suggests that omitted variables are positively correlated with both age and growth. Fourth, we observe a common pattern for the indicator variables identifying export status and public support to innovation. The estimated coefficients for the two variables both display positive and strongly significant association with firm growth in the POLS regression, in line with the expectation that there are differences across exporters and non-exporters and across "subsidized" vs. "non-subsidized" firms. Both the dummies loose however significance in the FE estimates: this upward bias of POLS estimates suggests, again as expected, that both exporting and receiving public funds tend to be positively associated with unobserved firm characteristics. Finally, our results reveal that group membership does not exert any statistically significant relationship with sales growth.

Next, Table 6 presents the estimates obtained with the indicators of product innovation. We first look at the dummy distinguishing firm that do perform product innovation from those that do not. POLS estimates (column 1) reveal a significant (at 5% level) difference in average growth across the two groups, with innovators displaying a 1% higher growth, on average. We find comparable patterns in POLS estimates for the two proxies looking at sales due to products new-to-the firm (col 3) and new-to-the-market (col-

Table 6: Regression analysis - Product Innovation

Dep.Var. is G_t	Innovation Proxy					
	Prod. Innov.		Prod.New-to-firm		Prod.New-to-MKT	
	POLS	FE	POLS	FE	POLS	FE
	(1)	(2)	(3)	(4)	(5)	(6)
INNOV_{t-1}	0.010**	-0.000	0.013**	-0.005	0.034***	0.015
	(0.005)	(0.009)	(0.007)	(0.009)	(0.011)	(0.014)
G_{t-1}	-0.187***	-0.314***	-0.187***	-0.314***	-0.188***	-0.314***
	(0.015)	(0.012)	(0.015)	(0.012)	(0.015)	(0.012)
$\ln Empl_{t-1}$	0.004	-0.162***	0.004*	-0.162***	0.004*	-0.162***
	(0.002)	(0.022)	(0.002)	(0.022)	(0.002)	(0.022)
$\ln Age_t$	-0.023***	-0.208***	-0.022***	-0.208***	-0.022***	-0.208***
	(0.004)	(0.057)	(0.004)	(0.057)	(0.004)	(0.057)
$Export_{t-1}$	0.024***	0.004	0.025***	0.004	0.025***	0.004
	(0.006)	(0.015)	(0.006)	(0.015)	(0.006)	(0.015)
$PubFund_{t-1}$	0.029***	0.005	0.030***	0.005	0.029***	0.005
	(0.005)	(0.007)	(0.005)	(0.007)	(0.004)	(0.007)
$Group_{t-1}$	0.005	-0.020	0.005	-0.020	0.005	-0.020
	(0.005)	(0.020)	(0.005)	(0.020)	(0.005)	(0.020)
Obs	26,386	26,386	26,386	26,386	26,386	26,386
Industry dummies	yes	yes	yes	yes	yes	yes
Year dummies	yes	yes	yes	yes	yes	yes

Notes: Estimates of Equation 3. Pooled OLS (POLS) and Fixed-Effects (FE) Robust standard errors in parenthesis. ***: significant at the 1% level; **: significant at the 5% level; *: significant at the 10% level.

umn 5). The estimated α is still positive and significant in both cases, but it is larger (0.034 vs. 0.013) and more strongly significant for innovations new-to-the-market. This seems in line with the interpretation that products new-to-the-market are more closely capturing true innovation, while products new-to-the-firm provide less value to the firm. However, the picture radically changes when we add firm fixed-effects. None of the product innovation proxies is statistically significant in the FE estimates, indeed (see columns 2, 4, and 6). The upward bias of POLS estimates is expected, since it is intuitive that time invariant uncontrolled factors, like efficiency or knowledge-related capabilities, are positively correlated with both sales growth and ability to introduce new products. The finding suggests that much of the contribution to sales growth coming from product innovation is related to the sticky components of product innovation efforts. The interpretation can be that product innovators tend to persistently introduce new products and non-innovators hardly can manage to become innovators over time, while at the same time the percentage contribution of new products to overall sales also remains quite stable over time.

The results on control variables are in full agreement with the patterns observed for the R&D proxies. We indeed find negative autocorrelation of sales growth, and a negative association of age with subsequent sales growth, irrespective of the estimation methods and of the product innovation proxy. Further, we again obtain a change from positive (barely significant) to negative (and strongly significant) coefficient on lagged size when comparing POLS and FE estimates. Moreover, we also observe, as before, that exporting firms and firms enjoying public support to innovation have higher subsequent growth than non-exporters and "non-subsidized" firms (cf. POLS results in columns 1, 3 and 5), while the correlation vanishes if we look at within-firm changes in export and "public support" status (columns 2, 4 and 6). Finally, group membership is 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. POLS results reveal that process innovators do grow more (2% on average, strongly significant), but the correlation vanishes in FE regression controlling for time-invariant firm characteristics. One interpretation can be that the role of process innovation is mediated by productivity. Activities intended to change production or delivery methods, and eventually the organizational setting, tend to enhance firm efficiency. However, as recently documented in several studies, higher efficiency does not necessarily maps into sales growth, one possible reason being that markets do not work as efficient selectors in allocating and redistributing resources in favour of the more efficient firms

Table 7: Regression analysis - Process Innovation and Embodied vs. Disembodied Tech. Change

Dep.Var. is G_t	Innovation Proxy					
	Proc. Innov.		Emb.Tech.Change		Dis.Tech.Change	
	POLS	FE	POLS	FE	POLS	FE
	(1)	(2)	(3)	(4)	(5)	(6)
INNOV_{t-1}	0.021***	-0.000	0.439***	0.350***	1.628***	0.957
	(0.005)	(0.009)	(0.088)	(0.125)	(0.549)	(0.730)
G_{t-1}	-0.188***	-0.314***	-0.188***	-0.313***	-0.188***	-0.314***
	(0.015)	(0.012)	(0.015)	(0.012)	(0.015)	(0.012)
$\ln Empl_{t-1}$	0.003	-0.162***	0.005**	-0.161***	0.004*	-0.162***
	(0.002)	(0.022)	(0.002)	(0.022)	(0.002)	(0.022)
$\ln Age_t$	-0.023***	-0.208***	-0.022***	-0.203***	-0.022***	-0.204***
	(0.004)	(0.057)	(0.004)	(0.056)	(0.004)	(0.056)
$Export_{t-1}$	0.023***	0.004	0.026***	0.004	0.026***	0.004
	(0.006)	(0.015)	(0.006)	(0.015)	(0.006)	(0.015)
$PubFund_{t-1}$	0.028***	0.005	0.028***	0.003	0.031***	0.005
	(0.005)	(0.007)	(0.005)	(0.007)	(0.005)	(0.007)
$Group_{t-1}$	0.005	-0.020	0.005	-0.020	0.005	-0.020
	(0.005)	(0.020)	(0.005)	(0.020)	(0.005)	(0.020)
Obs	26,386	26,386	26,386	26,386	26,386	26,386
Industry dummies	yes	yes	yes	yes	yes	yes
Year dummies	yes	yes	yes	yes	yes	yes

Notes: Estimates of Equation 3. Pooled OLS (POLS) and Fixed-Effects (FE) Robust standard errors in parenthesis. ***: significant at the 1% level; **: significant at the 5% level; *: significant at the 10% level.

(Bottazzi et al., 2008, 2010).

We observe the same variation across POLS and FE estimates also when we look at the proxy of disembodied technical change through acquisition of external knowledge (columns 5-6), the estimated α coefficients. Conversely, embodied technical change in the form of acquisition of new technological machineries (columns 4-5) has a positive and strongly significant coefficient irrespective of the estimation method. Control variables coefficients are in accordance with results obtained for R&D and product innovation proxies.

Summing up, we can deliver two main conclusions. First, across-firms comparisons tend to confirm the intuition that innovation positively correlates with firm growth, since all the different proxies for innovation activity indeed display positive and significant POLS coefficients. At the same time, however, FE results point out that the explanatory power (and the potential causal effect) of innovation on growth crucially depends from unobserved confounding factors. Overall, once controlling for firm fixed-effects, only *R&D* spending, especially if carried out internally, and investing in embodied technical change stand out as robust potential drivers of subsequent sales growth.[6]

5 Fixed-Effects quantile regressions

The distributional analysis provided in Section 4 recalls one of the major stylized fact of industrial dynamics, that is the huge heterogeneity in firm characteristics. As widely known, our response variable is characterized by a fat-tail distribution. This means that traditional regression analysis, capturing the behaviour of the "average firm", only deliver a partial picture. In this Section we turn therefore to a quantile regression approach, which allow us to explore the association between innovation strategies and growth along the whole spectrum of the growth rates distribution.

Quantile regressions have become popular in recent years in the literature on firm growth and innovation (see review in Section 2), allowing to uncover the asymmetries characterizing the growth-innovation relationship, with innovation having a stronger importance for faster growing firms. However, existing studies merely focus on a small set of innovation indicators (R&D

[6] To check whether results are driven by too little within-firm variation of the innovation proxies, we also performed a correlated random effect estimation, adding within-firm time series average of innovation variables and controls among the regressors. The coefficient estimates on the lagged innovation regressors remains practically unchanged as compared to the reported FE estimates. However, the coefficient on the average components, capturing the time invariant part of innovation, is positive and significant for all innovation proxies but external R&D and disembodied technical change.

and patents, essentially) and apply basic quantile regression methods, which are easy to implement, but come at the cost of not controlling for unobserved firm-specific factors. We exactly contribute along this direction, exploiting the quantile regression techniques recently developed in Canay (2011), explicitly allowing for firm-specific unobserved heterogeneity.

The method consists of a simple transformation of the response variable that allows to "wash out" a usual firm fixed-effect. Such transformation yields a consistent estimator, asymptotically Normal as n and T go to infinity.[7] Consider a standard panel setting:

$$\begin{aligned} Y_{i,t} &= X'_{i,t}\theta_u + \alpha_i + u_{i,t} \\ E(u_{i,t}|X_i, \alpha_i) &= 0 \end{aligned} \tag{4}$$

where the dependent $Y_{i,t}$ is the growth of sales, $X_{i,t}$ contains the set of explanatory variables (innovation indicators and controls), α_i is a firm fixed-effect, and $u_{i,t}$ a standard disturbance term. The Canay (2011) estimator proceeds in two steps: (i) estimate the individual fixed effect as $\hat{\alpha}_i = E_T[Y_{i,t} - X'_{i,t}\hat{\theta}_u]$, where $E_T(.) = T^{-1}\sum_{t=1}^{T}(.)$ and $\hat{\theta}_u$ is the standard panel within estimator of θ_u; (ii) build a transformed response variable $\hat{Y}_{i,t} = Y_{i,t} - \hat{\alpha}_i$ and then perform quantile estimation as in Koenker and Bassett (1978) on the transformed dependent variable, that is

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

We apply this methodology to re-estimate our baseline Equation (3), separately for each innovation variable. In Figure 3, 4 and 5 we provide a graphical representation of the across-quantile estimates of the main coefficient α. We show how the estimated coefficient on the innovation variables varies across the quantiles of the growth rates distribution, together with a 99% confidence band. This is obtained from bootstrapped standard errors, as recommended in Koenker (2004) and Canay (2011). To ease comparison with regression analysis from Section 4 we also report an horizontal line

[7]An alternative method is in Koenker (2004), correcting the estimation for the bias resulting from the possible correlation between the unobserved fixed effects and one or more regressors of the model. That solution rests on the assumption that the longitudinal dimension should be long enough to reduce the incidental parameter problem. In addition, the number of parameters to estimate is extremely large, which increases the computation burden and the risk of non-convergence. Canay's procedure can be implemented on short longitudinal data. The key assumption is that the fixed effects are location shifters, meaning they affect all quantiles in the same way.

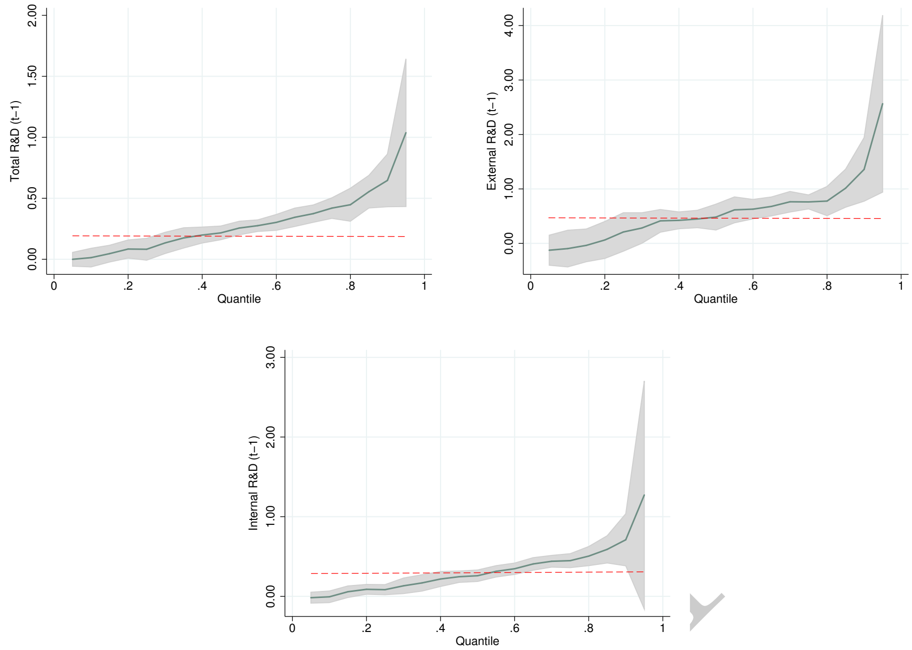

Figure 3: Fixed-effects quantile regression estimates of coefficient α from baseline equation 3, for different innovation proxies: Total, Internal and External R&D. Shadowed area represent 99% confidence band via bootstrapped standard errors. Horizontal line depicts FE estimates of α as benchmark.

indicating the estimated FE coefficient as benchmark.[8]

Figure 3 shows the results for the three R&D intensity proxies. The quantile regression curves reveal clear heterogeneity in the effect of each indicator across the conditional quantiles of the growth rates distribution. Against a positive coefficient estimated on the "average firm" from FE regression, two results are worth noticing here, no matter the proxy considered. First, for shrinking firms, i.e. at the bottom of the growth rates distribution, R&D expenditures do not have any statistically significant association with growth. Second, the coefficient estimates rise and become positive and significantly higher the the FE estimates in the upper quantiles. These asymmetries reveal that R&D provides a strong contribution to superior growth performance (i.e., for high-growth firms), no matter the indicator considered (the estimated coefficient on external R&D is twice as larger, but so does the standard error). The nil effect of R&D for firms belonging to the left tail

[8]See the Appendix for tables reporting the full set of coefficient estimates (innovation proxies and controls).

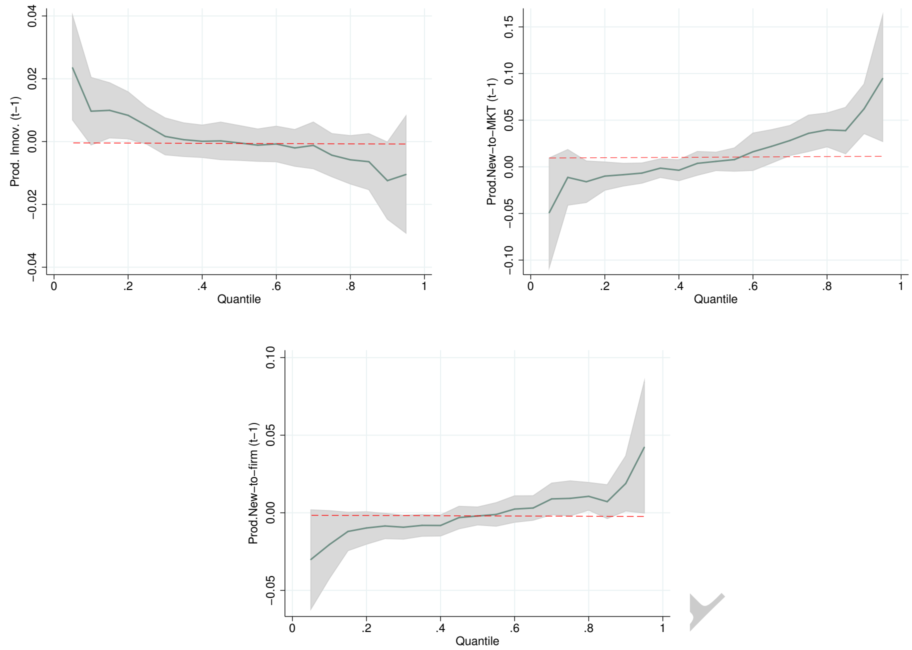

Figure 4: Fixed-effects quantile regression estimates of coefficient α from baseline equation 3, for different innovation proxies: product innovation dummy, % of sales due to products new-to-the-firm, and % of sales due to products new-to-the-market. Shadowed area represent 99% confidence band via bootstrapped standard errors. Horizontal line depicts FE estimates of α as benchmark.

is open to several interpretations. On one side the uncertainty of research often leads to unsuccessful outcomes (e.g. non tradable innovation), thereby making R&D efforts no more than a waste of resources. On the other hand, R&D activity may have some beneficial effect, but not strong enough to counteract the loss of market shares due to, for instance, a generally weak competitiveness of the firm in the market.

We comment on product innovation variables in Figure 4. The dummy variable proxing generic product innovation does not display any significant association with growth, in line with results from standard FE regression. This piece of evidence suggests that such qualitative information on whether a firm has introduced new products does not reflect the reaction of the market (e.g. the demand for a new product could be very low). Or, there might be a lag between introduction and commercialization. More informative findings emerge when we look at the effect of sales due to products new-to-the-firm or new-to-the-market. In both cases the quantile regression coefficients departs from the average picture offered by FE regression. For both variables, indeed,

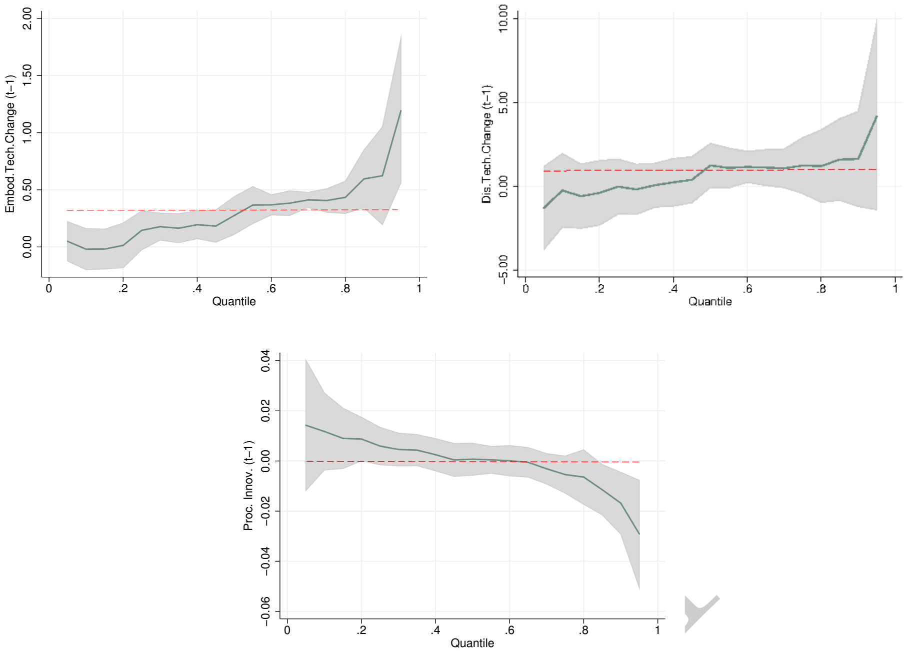

Figure 5: Fixed-effects quantile regression estimates of coefficient α from baseline equation 3, for different innovation proxies: Process Innovation, and Embodied vs. Disembodied technical change. Shadowed area represent 99% confidence band via bootstrapped standard errors. Horizontal line depicts FE estimates of α as benchmark.

there is no statistically significant association with growth for most of the quantiles, while the estimates turn positive and significant in the very top quantiles. This implies that, similarly to what observed for R&D proxies, product innovation is particularly important for high-growth firms. Noteworthy is the different magnitude of the estimated coefficients in the top quantiles: consistently with expectations, the ability to introduce products new to the market displays stronger association with sales growth than innovating in products which are new only for the firm.

Next, the top plots of Figure 5 report the findings about technological acquisition (embodied and disembodied technical change). The effect of embodied technical change turns from not significant to positive and significant starting from the median and to the upper quantiles. This confirms the crucial role of this type of innovation strategy already emerged from FE regressions. Conversely, disembodied technical change has not any significant coefficients across the entire spectrum of the growth rates distribution.

Finally, in the bottom plot of Figure 5, we confirm the result from FE regression that process innovation does not provide direct benefits in terms of sales growth. As already suggested in commenting FE regressions, this negative result may be due to the mediating role of productivity in between process innovation and growth. Here we can add that, if anything, the same result holds across most of the growth distribution quantiles, and that there might even be a mild negative effect among top-growing firms.

6 Conclusion

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. In this paper, by taking advantage of a rich panel on innovation activity of Spanish manufacturing firms, we explore the relationships between success on the market, in terms of sales growth, and a richer set of 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 contribute to expanding sales and market shares. First, results from standard regression analysis, especially controlling for firm fixed-effects, confirm the expectation that R&D represents a primar source of competitive advantage, being positively and strongly related with sales growth. The main qualification from our study is that both internal and external R&D play a role, but R&D activities performed within the firm have a clear stronger association with subsequent growth. There are several explanations for this finding. It can be related to the difficulties in establishing effective collaboration with external R&D providers, or to the lacking of specific absorptive capacities in integrating external research into the firm. Moreover, it can also be the case that firms tend to outsource only less-strategic R&D projects, while core and more valuable R&D is undertaken in-house. Second, from FE regressions we also robustly observe that embodied technical change, pursued in the form of acquisition of innovative machineries and equipment, stands out as a further major predictor of subsequent sales growth. This is a novel finding, never investigated before. Conversely, and third, FE estimates reveal that both product and process innovation, as well as disembodied technical change do not display any significant relationship with sales growth. The result on product innovation holds no matter whether we look at products new-to-the firm only or new-to-the-market. This is puzzling, since after all selling new products may be considered as the strategy more directly related to expansion and growth of sales.

This picture is complemented by the conclusions we can draw from fixed-effects quantile regressions. First, we confirm that R&D (total, internal and external) and disembodied technical change stand out as the main potential drivers of sales growth, and their contribution is particularly strong in top quantiles, that is for high-growth firms. Second, we can reconcile the evidence with the theoretical expectation that product innovation should correlate with sales growth. Indeed, we see that innovation in products new-to-the market has a positive and strong association with high-growth episodes. A similar finding, though weaker in magnitude, emerges for more imitative efforts resulting into introduction of products new-to-the firm. Finally, we confirm the lack of association between growth and the other innovation strategies considered, that is process innovation and disembodied technical change.

The research is of course open to further developments, in particular to account for the interactions among the different innovative activities we consider here. It might indeed be the case that growth comes from combinations of various innovation strategies, rather than from each single activity. Recent innovation studies (Mohnen and Roller, 2005; Catozzella and Vivarelli, 2014) provide evidence that the innovative inputs-output relationship may enjoy supermodular properties, arising from complementarities between some of the inputs and modes of knowledge sourcing which we also consider here. A natural step forward will therefore be to explore whether the innovation-growth relationship is equally characterised by complementarities and modularity.

We foresee two possible extensions along these lines. A first one directly working upon the distinction between innovative inputs. Afterall, R&D efforts (internal or external), acquisition of new machineries and acquisition of external knowledge all represent ways to build knowledge and competencies which serve as inputs in the generation of both product and process innovation. One could thus imagine to directly account for the differential ability of firms to link input and output of innovation, and then investigate how such different innovative configurations relates to growth on the market. This can be done within a standard Crepon et al. (1998) type of framework, modified to also explore complementarities and modularity. Second, and not at all un-relatedly, one can imagine to try and build taxonomies according to the "complexity level" of firms' innovative strategies. For instance, the relationship between growth and innovation maybe different for firms which are active in all layers (R&D, product and process innovation, acquisition of embodied and disembodied knowledge), with respect to firms that only performs one or two of these activities. Higher complexity probably rises more costs and challenging coordination issues, but at the same time can also offer stronger ability to capture and create growth opportunities. And complexity also means different things, from a more basic definition related to the mere number of different innovation activities performed ("full" vs. "partial innovators"), to a perhaps more interesting idea of complexity seeking to characterize how distant or closely related are the different combinations of innovation activities performed within each firm. Our results so far suggest that a combination of R&D, embodied technical change and product innovation, at least in product perceived as new for the market, is candidate to provide the more effective mix of growth-enhancing strategies, especially in view of their observed strong relationship with high-growth episodes.

Appendix

We here present tables reporting all coefficient estimates from fixed-effects quantile regressions applied to our baseline model in Equation(3). Graphical analysis of the results obtained for each innovation variable is presented in the main text. We remark here on the estimated coefficients on the set of controls.

Firstly, across all the specifications, that is irrespective of the innovation proxy considered, we observe a negative growth autocorrelation coefficient across all the quantiles. This result suggests that both all firms, either growing or shrinking in one year are unlikely to repeat the same growth performance in the following year. Second, and again robustly across different innovation indicators, we observe a negative correlation of size and age with sales growth. In both cases, moreover, the estimated coefficient is increasing (in absolute value) when moving from the left to the right tails of the growth rate distribution. The evidence connects to the well known finding that smaller and younger firms tend to grow faster, although the quantile profile here allows to add that the "detrimental effect" of age and size seems stronger for big positive jumps. Finally, across all the innovation dimensions, we observe some variability across quantiles in the coefficient estimates of the three control dummies on export status, public financial support and group membership. The export dummy plays a positive and significant association at lower quantiles, while the association becomes negative and significant for high-growth firms. This evidence recalls results in Hölzl (2009) who finds a negative relationship between export and growth performance in countries of Southern Europe (Italy, Portugal, Greece, Spain). Conversely, being part of industrial group is negatively related with sales growth across almost all quantiles, while it has a positive coefficient on the very top tail of the growth distribution. Public financial support to innovation does not have any significant relationship with sales growth, a result that might cast doubts on the effectiveness of such supporting schemes.

Table 8: Quantile regressions – Total R&D

	Quantile (%)				
	10	25	50	75	90
R&D$_{t-1}$	0.014	0.082**	0.256***	0.420***	0.646***
	(0.037)	(0.038)	(0.032)	(0.044)	(0.119)
G$_{t-1}$	-0.221***	-0.210***	-0.211***	-0.222***	-0.238***
	(0.019)	(0.009)	(0.010)	(0.010)	(0.013)
$\ln Empl_{t-1}$	-0.136***	-0.151***	-0.160***	-0.171***	-0.186***
	(0.003)	(0.002)	(0.001)	(0.002)	(0.003)
$\ln Age_t$	-0.135***	-0.153***	-0.167***	-0.179***	-0.197***
	(0.005)	(0.003)	(0.002)	(0.003)	(0.005)
$Export_{t-1}$	0.025**	0.010***	-0.000	-0.009*	-0.031***
	(0.010)	(0.004)	(0.003)	(0.005)	(0.010)
$PubFund_{t-1}$	0.006	-0.000	-0.007***	-0.006**	-0.016**
	(0.006)	(0.004)	(0.003)	(0.003)	(0.006)
$Group_{t-1}$	-0.054***	-0.030***	-0.023***	-0.015***	0.014**
	(0.008)	(0.004)	(0.003)	(0.004)	(0.007)
Industry dummies	Yes	Yes	Yes	Yes	Yes
Time dummies	Yes	Yes	Yes	Yes	Yes
Observations	26,386	26,386	26,386	26,386	26,386

Notes: bootstrapped standard errors in parenthesis. ***, ** and * indicate significance on a 1%, 5% and 10% level, respectively.

Table 9: Quantile regressions – Internal R&D

	Quantile (%)				
	10	25	50	75	90
Internal R&D$_{t-1}$	-0.006	0.083**	0.259***	0.448***	0.710***
	(0.047)	(0.037)	(0.038)	(0.053)	(0.127)
G$_{t-1}$	-0.225***	-0.209***	-0.211***	-0.223***	-0.236***
	(0.019)	(0.009)	(0.009)	(0.010)	(0.014)
$\ln Empl_{t-1}$	-0.136***	-0.151***	-0.161***	-0.171***	-0.186***
	(0.003)	(0.002)	(0.001)	(0.002)	(0.003)
$\ln Age_{t}$	-0.138***	-0.157***	-0.171***	-0.181***	-0.201***
	(0.005)	(0.003)	(0.002)	(0.003)	(0.005)
$Export_{t-1}$	0.026***	0.011***	0.000	-0.010*	-0.032***
	(0.010)	(0.004)	(0.003)	(0.005)	(0.010)
$PubFund_{t-1}$	0.006	0.000	-0.006**	-0.004	-0.015**
	(0.006)	(0.003)	(0.003)	(0.003)	(0.006)
$Group_{t-1}$	-0.054***	-0.030***	-0.022***	-0.014***	0.014**
	(0.008)	(0.003)	(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: bootstrapped standard errors in parenthesis. ***, ** and * indicate significance on a 1%, 5% and 10% level, respectively.

Table 10: Quantile regressions – External R&D

	Quantile (%)				
	10	25	50	75	90
External R&D$_{t-1}$	-0.096	0.209	0.483***	0.761***	1.358***
	(0.165)	(0.161)	(0.122)	(0.085)	(0.495)
G$_{t-1}$	-0.225***	-0.212***	-0.214***	-0.225***	-0.244***
	(0.019)	(0.009)	(0.009)	(0.011)	(0.015)
$\ln Empl_{t-1}$	-0.136***	-0.151***	-0.162***	-0.173***	-0.190***
	(0.003)	(0.002)	(0.001)	(0.002)	(0.003)
$\ln Age_t$	-0.159***	-0.180***	-0.194***	-0.208***	-0.230***
	(0.005)	(0.003)	(0.002)	(0.003)	(0.005)
$Export_{t-1}$	0.025**	0.010**	0.001	-0.010**	-0.029***
	(0.010)	(0.004)	(0.003)	(0.005)	(0.010)
$PubFund_{t-1}$	0.004	-0.001	-0.004	0.001	-0.005
	(0.006)	(0.004)	(0.002)	(0.003)	(0.006)
$Group_{t-1}$	-0.054***	-0.029***	-0.022***	-0.013***	0.015**
	(0.008)	(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: bootstrapped standard errors in parenthesis. ***, ** and * indicate significance on a 1%, 5% and 10% level, respectively.

Table 11: Quantile regressions – Product innovation dummy

	Quantile (%)				
	10	25	50	75	90
Prod.Innov$_{t-1}$	0.010	0.005	-0.000	-0.004	-0.012**
	(0.007)	(0.003)	(0.003)	(0.004)	(0.006)
G$_{t-1}$	-0.227***	-0.214***	-0.216***	-0.228***	-0.243***
	(0.020)	(0.009)	(0.009)	(0.010)	(0.015)
$\ln Empl_{t-1}$	-0.136***	-0.152***	-0.162***	-0.174***	-0.191***
	(0.003)	(0.002)	(0.001)	(0.002)	(0.003)
$\ln Age_t$	-0.169***	-0.192***	-0.206***	-0.220***	-0.244***
	(0.005)	(0.003)	(0.002)	(0.003)	(0.005)
$Export_{t-1}$	0.026**	0.009**	0.001	-0.010*	-0.029***
	(0.010)	(0.004)	(0.003)	(0.005)	(0.010)
$PubFund_{t-1}$	-0.003	-0.003	-0.003	0.005	0.006
	(0.006)	(0.003)	(0.003)	(0.003)	(0.006)
$Group_{t-1}$	-0.054***	-0.030***	-0.022***	-0.012***	0.016**
	(0.008)	(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: bootstrapped standard errors in parenthesis. ***, ** and * indicate significance on a 1%, 5% and 10% level, respectively.

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

	Quantile (%)				
	10	25	50	75	90
Prod.New-to-MKT$_{t-1}$	-0.011	-0.008	0.006	0.036***	0.062***
	(0.017)	(0.006)	(0.006)	(0.010)	(0.013)
G$_{t-1}$	-0.223***	-0.212***	-0.216***	-0.228***	-0.244***
	(0.019)	(0.009)	(0.009)	(0.010)	(0.015)
$\ln Empl_{t-1}$	-0.135***	-0.151***	-0.162***	-0.174***	-0.192***
	(0.003)	(0.002)	(0.001)	(0.002)	(0.003)
$\ln Age_t$	-0.170***	-0.192***	-0.207***	-0.221***	-0.242***
	(0.005)	(0.003)	(0.003)	(0.003)	(0.005)
$Export_{t-1}$	0.027***	0.011***	0.001	-0.012**	-0.036***
	(0.010)	(0.004)	(0.003)	(0.005)	(0.010)
$PubFund_{t-1}$	0.003	-0.001	-0.002	0.003	0.004
	(0.006)	(0.003)	(0.002)	(0.003)	(0.006)
$Group_{t-1}$	-0.056***	-0.031***	-0.022***	-0.012***	0.017**
	(0.008)	(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: bootstrapped standard errors in parenthesis. ***, ** and * indicate significance on a 1%, 5% and 10% level, respectively.

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

	Quantile (%)				
	10	25	50	75	90
Prod.New-to-firm$_{t-1}$	-0.020**	-0.009**	-0.002	0.009*	0.019**
	(0.009)	(0.004)	(0.004)	(0.006)	(0.009)
G$_{t-1}$	-0.224***	-0.211***	-0.217***	-0.226***	-0.244***
	(0.019)	(0.009)	(0.009)	(0.010)	(0.015)
$\ln Empl_{t-1}$	-0.135***	-0.151***	-0.162***	-0.174***	-0.192***
	(0.003)	(0.002)	(0.001)	(0.002)	(0.003)
$\ln Age_t$	-0.169***	-0.192***	-0.206***	-0.220***	-0.241***
	(0.005)	(0.003)	(0.002)	(0.003)	(0.005)
$Export_{t-1}$	0.028***	0.011***	0.001	-0.012**	-0.036***
	(0.010)	(0.004)	(0.003)	(0.005)	(0.010)
$PubFund_{t-1}$	0.001	-0.001	-0.003	0.004	0.004
	(0.006)	(0.003)	(0.003)	(0.003)	(0.006)
$Group_{t-1}$	-0.055***	-0.031***	-0.022***	-0.012***	0.017**
	(0.008)	(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: 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$_{t-1}$	0.012	0.006*	0.001	-0.005	-0.017***
	(0.007)	(0.004)	(0.003)	(0.004)	(0.006)
G$_{t-1}$	-0.224***	-0.215***	-0.216***	-0.228***	-0.241***
	(0.020)	(0.009)	(0.009)	(0.010)	(0.014)
$\ln Empl_{t-1}$	-0.136***	-0.152***	-0.162***	-0.175***	-0.191***
	(0.003)	(0.002)	(0.001)	(0.002)	(0.003)
$\ln Age_t$	-0.168***	-0.191***	-0.206***	-0.220***	-0.243***
	(0.005)	(0.003)	(0.002)	(0.003)	(0.005)
$Export_{t-1}$	0.024**	0.010**	0.001	-0.010*	-0.032***
	(0.010)	(0.004)	(0.003)	(0.005)	(0.010)
$PubFund_{t-1}$	-0.003	-0.003	-0.003	0.005	0.007
	(0.006)	(0.003)	(0.003)	(0.003)	(0.006)
$Group_{t-1}$	-0.053***	-0.031***	-0.022***	-0.012***	0.015**
	(0.008)	(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: 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$_{t-1}$	-0.019	0.145	0.275***	0.407***	0.623***
	(0.077)	(0.095)	(0.106)	(0.059)	(0.163)
G$_{t-1}$	-0.227***	-0.212***	-0.217***	-0.232***	-0.249***
	(0.019)	(0.009)	(0.009)	(0.011)	(0.014)
$\ln Empl_{t-1}$	-0.135***	-0.151***	-0.161***	-0.174***	-0.190***
	(0.003)	(0.002)	(0.001)	(0.002)	(0.003)
$\ln Age_t$	-0.165***	-0.187***	-0.202***	-0.215***	-0.237***
	(0.005)	(0.003)	(0.002)	(0.003)	(0.005)
$Export_{t-1}$	0.026**	0.011***	0.001	-0.008*	-0.032***
	(0.010)	(0.004)	(0.003)	(0.005)	(0.010)
$PubFund_{t-1}$	0.001	-0.002	-0.003	0.002	0.001
	(0.006)	(0.003)	(0.003)	(0.003)	(0.006)
$Group_{t-1}$	-0.053***	-0.031***	-0.022***	-0.012***	0.018**
	(0.008)	(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: 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$_{t-1}$	-0.249	-0.024	1.238*	1.230*	1.625
	(1.077)	(0.856)	(0.737)	(0.742)	(1.376)
G$_{t-1}$	-0.225***	-0.213***	-0.216***	-0.226***	-0.242***
	(0.020)	(0.009)	(0.009)	(0.010)	(0.015)
$\ln Empl_{t-1}$	-0.135***	-0.151***	-0.162***	-0.175***	-0.192***
	(0.003)	(0.002)	(0.001)	(0.002)	(0.003)
$\ln Age_t$	-0.166***	-0.189***	-0.203***	-0.217***	-0.239***
	(0.005)	(0.003)	(0.002)	(0.003)	(0.005)
$Export_{t-1}$	0.028***	0.010**	0.001	-0.011**	-0.033***
	(0.010)	(0.004)	(0.003)	(0.005)	(0.010)
$PubFund_{t-1}$	-0.000	-0.001	-0.002	0.004	0.004
	(0.006)	(0.003)	(0.003)	(0.003)	(0.006)
$Group_{t-1}$	-0.055***	-0.030***	-0.021***	-0.012***	0.017**
	(0.008)	(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: bootstrapped standard errors in parenthesis. ***, ** and * indicate significance on a 1%, 5% and 10% level, respectively.

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