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

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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 provide 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 innovative activity undertaken within firms. By taking advantage of a rich panel on innovation activity of Spanish manufacturing firms, reporting detailed CIS-like information continuously over the period 2004-2011, we are able to combine standard panel analysis with newly developed fixed-effects quantile regressions. The general picture emerging from the analysis suggests a good deal of heterogeneity in the ability of different innovation activities to support sales growth. R&D (especially external), embodied technical change (acquisition of innovative machinery and equipment) and to some extent product innovation (especially in products new to the market), have a positive relationship with growth, both on average and even more strongly for high-growth firms at the top quantiles of the growth rates distributions. Conversely, no effect is detected with respect to

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other innovation strategies, namely process innovation and disembodied technical change.

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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 key to determine the comparative advantages of firms over competitors, thus contributing to the ability of firms to gain market shares and grow. 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 uncertainty, risk taking, probing and re-probing, experimenting and testing. That is, the process of innovation itself, and the effects on various aspects of firm performance, can be extremely heterogeneous.

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 activity 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 have mostly focused and still are focusing 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 Hlzl (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 lies in 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 usually 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 particular dataset of Spanish firms available to us is a CIS-type dataset in terms of 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, no previous attempts exist in this direction.

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 and 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 can certainly be credited as one of the most investigated. However, the relationship between growth and innovation is still a puzzling topic. Indeed, whilst theoretical frameworks that relate these two dimensions of the company 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 what follows we try to 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 focus on studies investigating sales growth, which are more directly related to our analysis.[1]

The early papers documenting a relationship between growth and inno-

[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. We do not discuss this literature here, as we are more interested in a measure of growth capturing success on the market.

vation 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 grew faster. Similar results are found also by Scherer (1965) who analyze the patenting activity of the 365 largest US companies, and Mowery (1983) that looks 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 firm over a panel of more than ten years. After having identified those companies that introduced at least a major innovation, they conclude that innovating firms are characterized both by higher profitability and faster grow than their non-innovators counterparts. Interestingly enough, they also note that the increase of sales is transitory, until the firm loses proprietary control over the new knowledge employed. Storey (1994) corroborates these finding underlining also the important magnifying role played by the initial size, with smaller firms achieving a more rapid growth after having been successful in innovating. On the same token, by categorizing 228 small UK manufacturing firms considering different level of innovation, Freel (2000) shows that, although innovation does not necessarily determine firm growth, it may be relevant in boosting high-growth. Stam and Wennberg (2009) explicitly target new start-ups showing 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 significant effects of innovation on firm growth (among the others, see Geroski et al. 1997; Geroski and Mazzucato 2002). Particularly relevant for the level of detail of the data (product-level) is the contribution of Bottazzi et al. (2001). They target the top world 150 firms operating in the pharmaceutical sector, 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 its sales growth.

The difficulties of empirical studies at identifying any strong link between innovation and sales growth might be related to the extreme complexity of the firms innovative process. In turn, an extremely robust stylised fact emerging from the industrial economic literature is that growth rates distributions are characterised by wide heterogeneity and a tent shape (among the many see Stanley et al. 1996; Bottazzi and Secchi 2006; Coad 2009 for a detailed survey), whatever the level of sectoral disaggregation one accounts for (Dosi, 2007). In this respect, for its inherent nature, the transformation 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. In order to account for this issue, recent empirical contributions has focused on quantile regression techniques that allow to disentangle the effect of innovation on the entire distribution of growth rates (and not simply on the 'average' firm). Coad and Rao (2008) restrict their focus on four sectors with fast changing technologies. They 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 greater benefits from their innovative efforts. A number of subsequent studies followed this approach, with the main focus on those companies typically labeled as high-growth or 'gazelle' firms. For instance, Hlzl (2009) exploits the information from CIS III data for 16 countries, grouping them in three categories based on their stage of technological development. He finds 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 new 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. However, despite these important methodological progresses, the literature is still underdeveloped under several respects. In particular, as recently emphasized by Audretsch et al. (2014), the high level of complexity of R&D along with the large variety of innovation strategies that a firm has at its disposal, call for a multidimensional approach to assess the actual contribution of different innovation activities on corporate growth. Despite the increasing availability of more comprehensive and precise data, studies on the subject are still focusing on traditional proxies such as R&D and patents.

If we consider the output side of innovative activity, it is now recognized that patents may not be the only measurable result of innovation, opening the way to the direct investigation of the role of product and process innovations (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 product innovation may be considered as the most important strategy for expansion and growth (Hay and Kamshad, 1994). Notwithstanding, within studies seeking to link innovation and sales growth only few works have considered proxies of innovative output alternative to patent. Among these, of particular interest is the above-mentioned contribution of Hlzl (2009), where, besides R&D, the focus is 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, apart from R&D, also innovative success (share of products new to the market) is of great importance for high-growth firms, in particular for those located in countries closer to the technological frontier. By the same token, Corsino and Gabriele (2011), focusing on a worldwide sample of high-tech firms, find that incremental product innovations introduced in the recent past positively affect sales growth.

On the other hand, the possible beneficial effect of process innovation, is less obvious. Indeed, while there is a large literature providing convincing evidence of the important role played by this type of innovation activity in enhancing firm productivity (see for exampleGriffith 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, the only exception is represented by a recent work of Goedhuys and Veugelers (2012) that analyses the growth determinants of a sample of Brazilian manufacturing firms. The authors test a recursive model allowing to simultaneously assess the relevance of different firm R&D strategies (internal development and external acquisition) in shaping innovation output and the impact that successful new processes or products have in stimulating growth. The results show that, unlike product innovations, the realization of process innovations has no effect on sales growth. They interpret this particular evidence by asserting that more cost efficient production may show its beneficial effects on sales in a later stage after an initially period of restructuring, having instead a more immediate influence on other dimensions of firm performance such as productivity.

Moving the attention to the 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, in turn calling for a more comprehensive attempt to widen the scope of research to activities like outsourced R&D, technological acquisition in its embodied (investment in machinery and equipment) and disembodied components, for which quite rich dataset are now available. The only study that moves in this direction is the recent work by Segarra and Teruel (2014). Although the main goal of their contribution is to analyze the general impact of R&D on firm growth, they also provide interesting evidence that while formalized R&D shows a significant positive impact in the upper quantiles of the growth sales distribution, external R&D appears to be important only up to the median. To best of our knowledge, there is no evidence, instead, about the impact of both embodied and disembodied technical change in boosting firm sales growth. This is quite unfortunate, given the central role played by these activities in determining innovation success of firms. Santamara et al. (2009), for example, by making use of a large panel of Spanish manufacturing firms 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 the embodied technological change in fostering firm innovative success (measured as share of total turnover stemming from the sale of new or significantly improved products). Moreover, they show also that the impact of this activity beyond formal R&D is especially important in low-tech industries, and for small and young firms.

The ultimate goal of this paper is precisely to cover these gaps in the literature by looking at the impact of a wide range of innovative indicators on firms' sales growth.

3 Data and descriptive analysis

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

3.1 Data and sample

In this paper we use firm level data drawn from the Spanish Technological Innovation Panel (henceforth PITEC), realized jointly 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 to constitute 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 and marketing.

An important peculiarity that distinguishes PITEC from the majority of European CIS-type datasets is its longitudinal nature. Indeed, since 2003 systematic data collection has ensured the consistent representativeness of the population of Spanish manufacturing and service firms over time. This characteristic represents an important methodological advantage because allows us to control for unobserved factors that could have an impact in determining the firm growth pattern.

In this study, we consider survey data for the period 2004-2011 and select our working database from an initial sample of 100,016 firm-year observa-

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.

tions. 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 only look at organic growth, while 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 the empirical analysis (see below).

Table 1 depicts the composition of the final unbalanced panel made up of 26,386 year-observations. As can be seen, a notable fraction (around 62%) out of a total of 5,064 firms included in the final sample are observed over the entire period, around 20% for 7 period and only a negligible percentage (7,31%) for less then 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.

We relate firm growth to innovation behavior and performance by adopting a multidimensional approach. That is, we consider a set of different variables providing information about firm's engagement in different types of innovation activities and the results of this engagement in terms of innovation success. More precisely, we employ the following 9 indicators:

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 identifying those firms that have introduced new or significantly improved products.
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 identifying those firms that have introduced new or significantly improved processes.
8. Embodied technological change (intensity): Investments 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 case well accepted. R&D proxies just measure expenditures in different R&D activities, and we also follow the usual approach to take the ratio to total turnover instead of absolute figures. The binary categorization between product innovators and non-product innovators is also quite standard. Less

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.

commonly used are instead the two variables built from sales related to products new-to-the-firm or new-to-the market. Although highly correlated, these measures are usually interpreted as proxies for two distinct modes of product innovation. The introduction of new product into the market connects with the ability to perform "true innovation" resulting in more valuable products, whereas products new only to the firm are more connected with imitation strategies. Process innovation is a further quite common indicator of innovation output, with standard interpretation as capturing reorganization of production or implementation of new processes. The focus in previous studies is specifically on the direct relationship between this variable and firm efficiency, whereas the indirect relationship to growth is less investigated. We also follow the common practice to interpret acquisition of new machineries and of external knowledge as proxies of embodied and disembodied technical change.

Table 2 depicts some descriptive statistics for the 9 indicators. As can be seen, firms in our sample seem to be more prone to perform 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 is close to 0 in the case of investment in disembodied technological change. However, by looking at the other statistics, it can be inferred that innovation intensity displays a very skewed distribution. Among the indicators of innovative output, it seems that firms are equally oriented towards products and process

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.

innovation, around 63% of the sample having introduced both types of innovative output. On the other hand, the share of firm's total sales generated by products new to the market is much lower (on average) than the share of sales stemming from products that are new only to the firms (9.9% *vs* 24.8%).

3.3 Preliminary evidence

To provide a preliminary picture of the relationship between sales growth and innovation we focus on each individual innovation variable splitting our sample into two subgroups of "innovators" and "non-innovators" along each

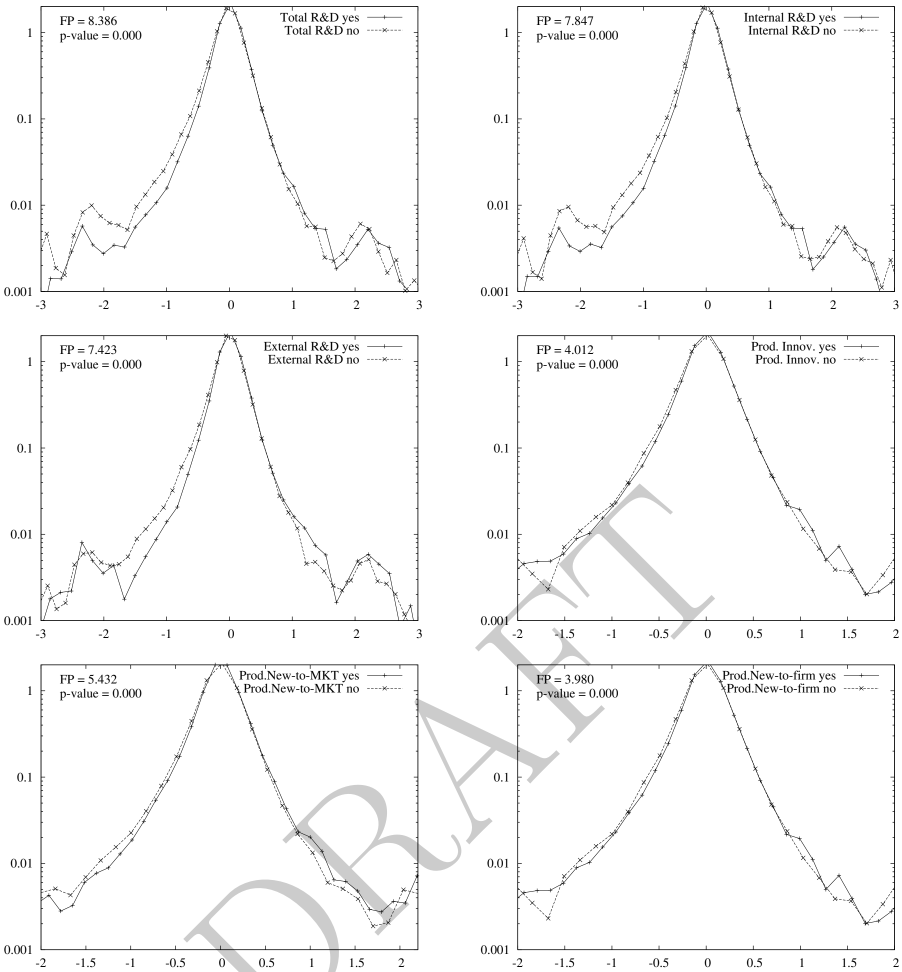

Figure 1: Kernel estimates of sales growth rates densities by innovation proxy: Total, Internal and External R&D; and Product innovation, also distinguishing between products new-to-the-firm or new-to-the-market. Figures also report Fligner and Policello (1981) test of stochastic dominance for comparison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

innovation proxy. Precisely, we compare growth performance across firms that adopt a specific innovation strategy versus firms that do not.[2]

[2]The latter might be however innovative firms, in the sense that they might invest in other types of innovative activities.

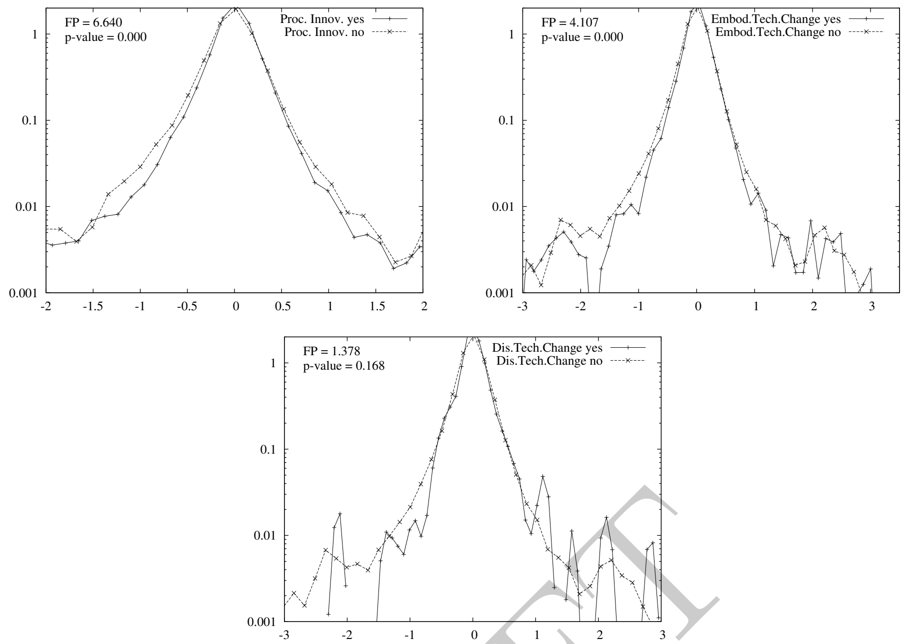

Figure 2: Kernel estimates of sales growth rates densities by innovation proxy: Process Innovation, and Embodied vs. Disembodied technical change. Figures also report Fligner and Policello (1981) test of stochastic dominance for comparison between "innovators" and "non-innovators", defined as firms that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

Table 3 reports basic descriptive statistics across different subgroups. Interestingly it may be noticed that subsamples are quite homogeneous in terms of size (except for embodied and disembodied technological change, which clearly represent the least frequently adopted strategies). Further, innovators appear to display larger mean and median growth rates than non-innovators, regardless the innovation variable.

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. The estimates, reported in log-scale, indicate some differences between innovative and non-innovative firms. The shape of the distributions differ, in particular, with non-innovative firms generally more concentrated in the left part of the support. Asymmetries in the left tail are particularly pronounced when R&D activity (total, internal or external) is used as discriminatory variable. In most of the cases, less clear cut is the difference in the right tail, implying that non-innovative firms are nevertheless subject to 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 innovative firms present a higher probability of experiencing superior growth performances than their non-innovative counterparts.

Overall, the evidence seems to point at a positive association between sales growth and innovation behavior, along all the different dimensions we consider.

4 Regression analysis

Our modeling strategy is to explore the relationship between firm growth and each different proxy of innovation activities undertaken by firms. 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 the each innovation variable that we can measure in the PITEC dataset, while $\mathbf{X}$ is a set of control variables. Both INNOV and all the controls enter with a 1-year lag, at least partially controlling for potential simultaneity.[3] The 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.[4] Table 4 reports the corresponding descriptive statistics. All the specifications also include a full set of industry and year dummies.

[3]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.

[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 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.

The coefficient of main 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 characteristics that PITEC data records (as 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. Similar reasoning apply 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 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.

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.

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 sales, 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 which are likely positively correlated 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 the two variables 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. Also, they can be revealing of little within-firm over time variation of the two controls: over time, exporters tend to remain exporters, and public funds tend to be persistently granted to a firm, at least on average. 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 our three measures of product innovation. We first look at a simple 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, other factors being equal. A similar result is maintained in POLS estimates when we instead look at the two innovation proxies recording the contribution to total firm turnover of introduction of products new to the firm (col 3) or new to the market (column 5). Estimated α is still positive

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.

and significant in both cases, but the correlation is higher ($\alpha = 0.034$ vs. $\alpha = 0.013$) and stronger (significant at 1%) 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 are more likely resulting from imitative efforts, thus providing less value to the firm. When we control for unobserved heterogeneity, however, the picture changes and all the product innovation proxies turn out as not significant (respectively in 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 FE estimates suggest that much of the contribution to sales growth coming from product innovation is related to the sticky components of product innovation efforts. In other words, 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 financing of 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 relationship with sales growth.

In Table 7 we report the estimates concerning the other innovation proxies. In columns 1-2 we exploit the binary indicator of whether a firm does or does not undertake process innovation. POLS 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

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.

favour of the more efficient firms (Bottazzi et al., 2008, 2010).

When we look at the proxy of disembodied technical change through acquisition of external knowledge (columns 5-6), the estimated α reveal the same variation across POLS and FE estimates. 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 display patterns in accordance with results obtained with the product innovation regressors.

To sum up, the regression analysis delivers two main conclusions. First, we can confirm the intuition that innovation tends to be positively correlated with firm growth, since all the different innovation activities indeed display positive and significant POLS coefficients. At the same time, and second, such correlation can be severely affected by confounding factors and, in particular, the explanatory power (and the potential causality) of innovation proxies on growth crucially depends from time invariant idiosyncratic factors. Overall, among the various type of innovation modes and efforts observed in the data, only *R&D* spending, especially if internal, and investing in embodied technical change stand out as robust potential drivers of subsequent sales growth.[5]

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 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 regression has 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,

[5] 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.

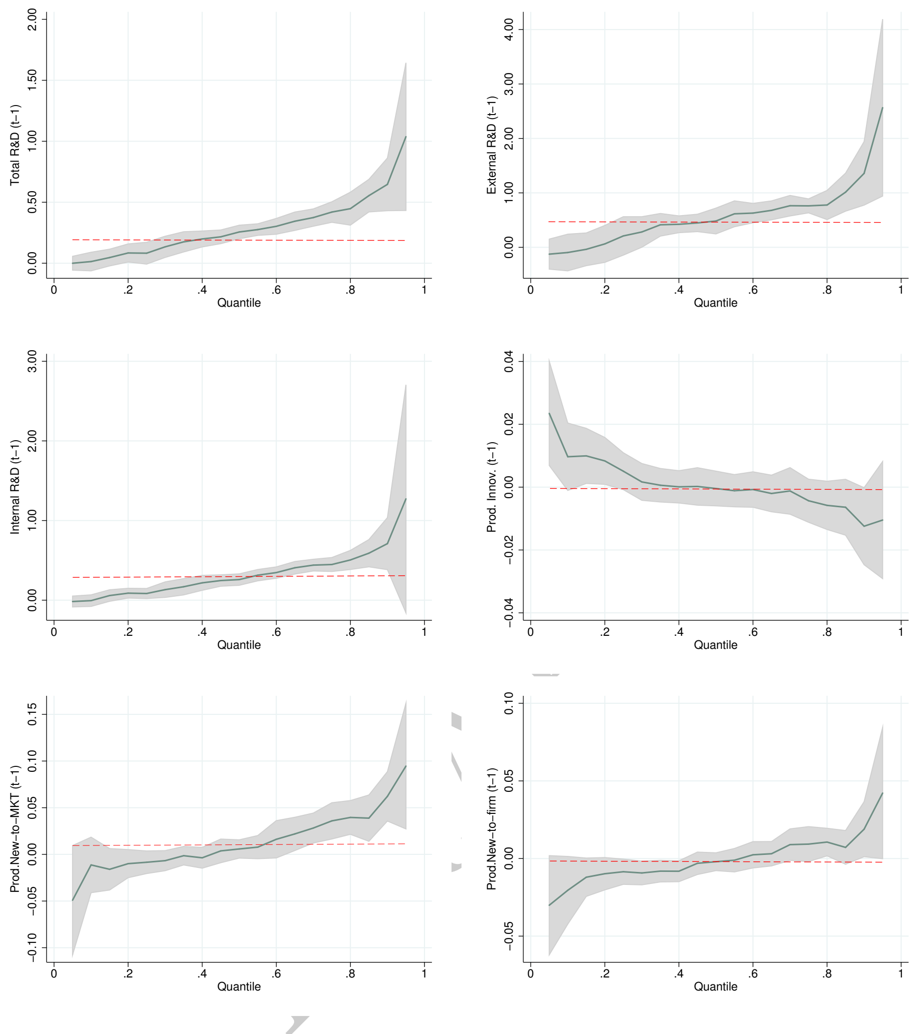

Figure 3: Fixed-effects quantile regression estimates of coefficient α from baseline equation 3, for different innovation proxies: Total, Internal and External R&D; and Product innovation, binary indicator and distinguishing between products new-to-the-firm or new-to-the-market. Shadowed area represent 99% confidence band via bootstrapped standard errors. Horizontal line depicts FE estimates of α as benchmark.

existing studies merely focus on a small set of innovation indicators (R&D and patents, essentially) and apply basic quantile regression methods, that are easy to implement, but come at the cost of not controlling for unobserved firm-specific factors. We exactly contribute along this direction, exploiting different quantile regression techniques that do control for unobserved het-

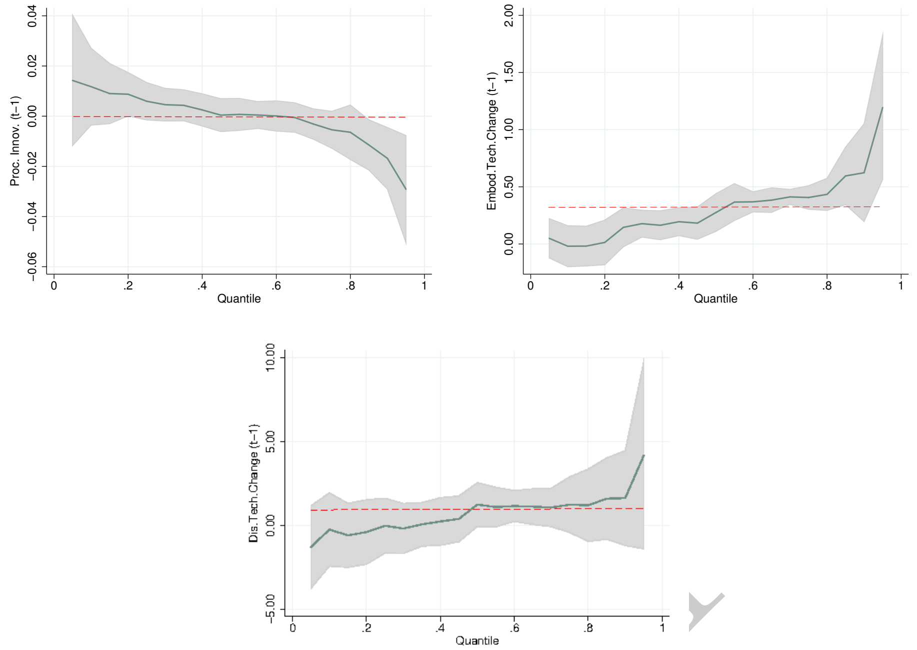

Figure 4: Fixed-effects quantile regression estimates of coefficient α from baseline equation 3, for different innovation proxies: Process Innovation, and Embodied vs. Disembodied technical change. Shadowed area represent 99% confidence band via bootstrapped standard errors. Horizontal line depicts FE estimates of α as benchmark.

erogeneity recently developed in Canay (2011).

The method consists of a simple transformation of the response variable that allows to "wash out" the unobserved fixed effects. Such transformation yields a consistent estimator, asymptotically Normal as n and T go to infinity.[6]

Let consider a standard panel setting

[6] 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.

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

where $i = 1, ..., n$ and $t = 1, ..., T$ represent the indexes of firms and time periods; $Y_{i,t}$ is the response variable (growth of sales);the vector $X_{i,t}$ contains the set of explanatory variables; the firm-specific constant α_i is a firm fixed-effect, and $u_{i,t}$ is a disturbance term. The estimator presented in Canay (2011) 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

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

We apply this methodology to re-estimate our baseline Equation (3), separately for each innovation variable. As common, we provide a graphical representation of the estimation results. In Figure 3 and Figure 4 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 of Section 4 we also report an horizontal line indicating the estimated FE coefficient as benchmark.[7]

Let us focus first on the R&D intensity proxies, total, in-house and external R&D (Figure 3). 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, R&D expenditures do not have any significant association with growth for shrinking firms. Second, the coefficient estimates rise sharply and monotonically from the lower to the upper quantile. These asymmetries reveal that R&D provides higher contribution to firms with superior growth performance (i.e., for high-growth firms), and such effect is particularly pronounced when firms undertake external R&D activities (the estimated coefficient is almost twice as larger). The nil effect of R&D for firms belonging to the left tail can be connected to diverse interpretations.

[7]See the Appendix for tables reporting all point estimates for the entire set of explanatory variables (innovation proxies and controls).

On one side the uncertainty of the research and innovation often leads to unsuccessful outcomes (e.g. non tradable innovation), thereby making innovative efforts no more than a waste of resources. On the other hand, the R&D efforts may have some beneficial effect, but they are not enough to stop the shrinking of market shares, for instance because the efficiency of the firm is so low that the company is not competitive on the market.

We next focus on product innovation variables (see again Figure 3). The dummy variable proxing overall product innovation does not provide any significant estimate, 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 the two more quantitative measures of innovative output, the share of sales due to products new-to-the-firm or new-to-the-market. In this case quantile coefficients depart from the average picture offered by FE regression. For both variables, indeed, there is no statistically significant effect at the median, while their associated coefficient turns positive and significant for the top quantiles. This implies, similarly to what observed for R&D proxies, that product innovation can be particularly important for high-growth. 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. There is instead a peculiar behavior in the left side of the support for the share of sales from products new to the firm. For shrinking firms, indeed, the estimated coefficient is negative. A temptative interpretation is that shrinking firms try to survive to market selection by imitating competitors and readjusting their product range, but competitive pressure is however too strong and hampers a recovery.

Next, in Figure 4, we report results about technological acquisition in its embodied and disembodied components. The effect of the first component rises sharply starting from the median onward, and the result confirm the crucial role of this type of innovation strategy already emerged from FE regressions. Conversely, we cannot detect any statistically significant effect in the lower quantiles. Disembodied technical change has a barely significant coefficients only on the “median firm”. This evidence might be consistent with the idea that young and fast growing companies do not generally adopt this innovation strategy.

Finally, we confirm the results from FE regression that process innovation do not provide direct benefits in terms of sales growth (Figure 4, bottom plot). This negative result, as already suggested in commenting FE regressions, may be due to the mediating role of productivity in between process innovation and growth. Here we can add that the same result holds across the entire growth distribution.

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 provide 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 multidimensional account of innovation behavior and performance of firms. We indeed correlate sales growth with a series of innovation indicators and variables, capturing innovation inputs and outputs as well as modes of knowledge sourcing.

The overall picture emerging from the analysis suggests a good deal of heterogeneity in the ability 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 related to establish 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 changed, 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 new finding, never investigated before. Conversely, and third, FE estimates reveal that neither disembodied technical change nor product innovation have 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 find that the positive contribution of R&D (both internal and external) is particularly strong for high-growth firms. Similarly strong is also the effect of embodied technical change in the top quantiles. These two factors stand out as the main potential drivers of sales growth, and of high-growth in particular. Second, we can reconcile the evidence with the theoretical expectation that product innovation should correlate with sales growth. In particular, indeed, we see that innovation in products new-to-the market do have a positive and strong association for high-growth episodes. Similar finding, though weaker in magnitude, emerges for innovation in products new-to-the firm. Finally, we confirm the lacking of any association between growth and the other innovation strategies: process innovation and disembodied technical change.

The research is of course open to further development, in particular to account for the interactions among the different innovative activities we consider here. We foresee two possible extensions. A first one along the distinction between innovative inputs and innovative outputs. Afterall, R&D, embodied technical change through acquisition of new machineries and acquisition of disembodied knowledge represent different and complementary ways to build knowledge and competencies which serve as inputs in the generation of both product and process innovation. One could thus imagine to account more directly 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. 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. And this avenue might be interesting to explore not only in terms of how many innovation activities are performed ("full" vs. "partial innovators"), but perhaps more importantly with respect to the firm-specific combination of different modes of innovation. Our results so far tend to suggest that a combination of R&D, embodied technical change and product innovation, at least in product perceived as new for the market, can provide the more effective mix of growth-favoring activities, especially in terms of their positive 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 Hlzl (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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