Does persistence of innovation spur persistence of growth?

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Abstract

In this paper we examine whether persistence of innovation plays an effect on persistence of growth performance. Exploiting a rich panel of Spanish companies comprising information about firms and market characteristics, we empirically assess whether a systematic engagement in innovation activities induces more structure and regularity in the process of firm growth. We build our theoretical background drawing from models of firm-industry dynamics as well as from the strategic management literature, arguing that companies are likely to achieve sustained growth only when they persistently, and not just occasionally, broaden their technological capabilities. We do find support to this conjecture as our analysis shows that persistent innovators are those economic actors which display a higher tendency to persistently expand their size. A series of additional robustness checks show that other firm-level characteristics, age and size in primis, do play only a minor role.

1 Introduction

This paper examines the role of persistence of innovation on persistence of growth at the firm-level. The main issue we address in our study is to empirically assess whether a systematic, rather than a sporadic, engagement in innovation activities induces a less erratic structure in the process of firm growth, or put more simply, whether persistent innovators exhibit persistently superior growth performance.

For the best of our knowledge this is the first attempt linking more explicitly the evidence on the patterns of innovation with what is known about persistent growth.The lack of empirical regularities on the subject is, however, somewhat surprising since in the last decades two abundant streams of literature, one focused on persistence of growth, the other on persistence of innovation, have been developed in parallel but never reconciled one another.

Concerning the former, contributions from economics and management help in providing theoretical conjectures on why some firms persistently outperform in our economy. The rationale can be simplified as follows: efficiency (or productivity) is the central channel through which companies achieve growth and gain market shares at the expenses of less efficient units, either directly because higher efficency gets reflected into lower prices, or indirectly because higher efficiency implies increasing profits which, in combination with sounder financial conditions, grant the access to additional resources needed to further investments (among the many contributions see the primordial discussion in Penrose, 1959, or the theoretical models of firm-industry evolution with heterogeneous agents as in Nelson and Winter, 1982; Jovanovic, 1982; Cooley and Quadrini, 2001). Higher efficiency is assumed to be strongly related to more attractive firm-specific unobserved factors, technological and organizational traits in primis. These dimensions create value for consumers, are unique (or at least not identical than that possessed by rivals), durable, not (in principle) inimitable, and generate returns which are appropriable (Teece et al., 1997; Teece, 2007). Therefore, the degree of persistence in the process of growth that one should observe is connected to the structural competitive advantages (comparative and differential) that the firm exploits over time, at least until the fingerprint of market competition erodes such advantages (Geroski, 2002).

Persistence of innovation also finds several theoretical explanations. The "success breeds success" hypothesis is perhaps among the most accredited: succesful innovation broadens both a firm's technological opportunities and its market power which, in turn, positively affect the conditions for subsequent innovations (Flaig and Stadler, 1994). In addition to that, the cumulative and additionality nature of technological knowledge is such that firms are likely to experience some dynamic increasing returns in their innovation activities (Stiglitz, 1987). Some scholars have put forward interpretations related to a process of learning by innovating which enhance knowledge stocks and technological capabilities, at last inducing state dependence in innovation behaviour (Dosi et al., 2008). Finally, innovation activities are typically characterized by high start-up sunk costs which are necessary to set up the entire R&D apparatus (research infrastructures and the staff), thus once the decision has been taken, the opportunity costs to stop are typically too high (Sutton, 1991).

There exists a vast literature linking growth events to innovation potential and, certainly, the latter is considered by economists and scholars from strategic management tradition as one among the key competitive tools. However the degree of persistence in innovation which is necessary to build durable competitive advantages, that in turn might get reflected into sustained sales expansion, is somewhat under investigated and some questions remain still unanswered. Are firms that systematically engaged into innovation activities those firms experiencing more structured (or persistent) growth patterns? Or, on the opposite, can a sporadic innovative behaviour be sufficient to overcome competitors over long periods of time? Answering these questions is relevant to understand to what extent, and how quickly, market competition erodes the competitive advantages that firms build upon their innovation success, as well as the longlasting consequences that different innovation behaviours may induce.

Against this background the research question that we pose in this essay is the following: does persistence of innovation spur persistence of growth?

To answer to this question we exploit a rich panel of Spanish firms comprising micro-level information about firms and market characteristics and spanning a period of twenty years, from 1990 to 2009. We empirically investigate the determinants of persistent sales growth by mean of duration model techniques: more precisely, we relate the probability and the length of a period of continuous positive growth (what we will define as "growth spell") to the "innovation status" defined in a time window prior the persistent expansion. We build the innovation status of each firm on the basis of the frequency with which it undertakes R&D activities or applies for patents, in turn distinguishing three distinct categories of firms: non-innovators, occasional, and persistent innovators.

Although we do observe striking differences among groups, being persistent innovators generally larger, older, more productive and active in high-tech sectors, we find weak support to the conjecture that a systematic engagement in R&D activities is beneficial to persistent sales expansion. However, when we focus on innovation outcome, proxied by patent applications, we do find a positive and significant association between persistence of innovation and persistent of growth performance. Put it differently, we observe that firms who persistently innovate display subsequent longer periods of sustained positive growth. These findings are robust to a number of extensions and alternative definitions of the innovation status. All in all our evidence suggests that a firm's competitive advantages have a higher propensity to be sustainable only if the firm is able to persistently, and not just occasionally, broaden its technological capabilities.

The rest of this document is structured as follows. In Section 2 we provide a review of the literature, with particular emphasis on the results from previous empirical studies targeting firm-level persistence of growth and innovation. Section 3 contains a description of our data, the criteria to define persistent growers and persistent innovators, and the empirical setting that we design. In Section 4 we present our econometric analyses and discuss the main evidences. Section 5 concludes.

2 Background literature and research objectives

2.1 On the persistence of innovation

Although, as discussed in the previous Section, the theoretical literature provides several explanations supporting the path-dependent and persistent nature of innovation, the empirical evidence is far from conclusive. The latter is indeed very dependent on the proxy of innovation considered (i.e. input vs. output measures) as well as on data specificities (i.e. country, industry).

The vast majority of the empirical literature on the subject has focused on the output side of the firm's innovation activity, relying on different measures such as patents, share of sales stemming from innovative products, and realization of process and/or product innovations.

Patent-based studies, on average, have largely found little evidence of persistence. Malerba and Orsenigo (1999), using European Patent office (EPO) data for 6 different countries, find that only a negligible proportion of firms persist in its patenting activity. Interestingly, the number of patents granted to these firms increase exponentially over time, suggesting that persistent innovators, although few in number, are responsible for a very large share of total patents. Along the same line, Geroski et al. (1997), drawing upon a representative sample of UK innovative firms observed for the period 1969-1988, come to similar conclusions: very few firms innovate persistently, and they do so only after reaching an initial threshold of five patents. Cefis and Orsenigo (2001) and Cefis (2003), applying a non-parametric approach on EPO data, further corroborate this evidence. Their results show also that persistence varies greatly across industries and size dimensions.

As well known, patent is a peculiar proxy of innovation activity since only a very small percentage of inventions are actually patented. This might, to some extent, explain the low level of persistence of innovation detected by previous studies. At the same time, persistence measured using patent data has the advantage to implicitly indicate persistence of innovative leadership (Duguet and Monjon, 2004) and, as we will point out later in this Section, this issue is particularly relevant in our context.

Other scholars have focused on less demanding indicators of innovative success, such as the realization of products and process innovations and the share of innovative sales. König et al. (1994) and Flaig and Stadler (1994), using a panel of German manufacturing firms find support of high persistence for both process and product innovations. Raymond et al. (2010), by applying a dynamic two-type tobit model on Dutch CIS panel data, provide evidence of state dependence only in the high-tech industries. A similar conclusion is reached by Antonelli et al. (2012) which, accounting for complementarity effects between the product and process innovation, find robust evidence of persistence for Italian companies.

Finally, some contributions have considered the input side of the innovation activity, analysing the degree of persistence of R&D activities. In this respect, regardless the econometric methodology and the data used, a high level of persistence in innovation activity is detected (see Peters 2009; Mañez et al. 2009; Arqué-Castells 2013; García-Quevedo et al. 2014; Triguero et al. 2014). Unlike output proxies, measures of innovation input denote the firm's willingness to realize any type of innovation, rather than exclusively success in achieving such innovation. In this context, as previously discussed, the high degree of persistence in R&D is very likely to be induced by specific industry barriers such as start-ups sunk costs (Sutton, 1991; Mañez et al., 2009).

2.2 On the persistence of growth

Persistence of firms' differentials is a widely investigated topic in the industrial economic literature. Perhaps one of the major stylized fact emerging from the vast body of empirical studies is that firms persistently differ, even within the same lines of activities, in their productivity and profitability. Much more controversial is the evidence on persistence of corporate growth.

At the theoretical level, as discussed in Section 1, one should expect some structure in the growth process. The conjecture is relatively straightforward: competitive advantages are at the basis of growth and the presence of such advantages relies upon the possession of finest resources, routines, technological and organizational capabilities. All these core competencies create value on the market, are typically unique (or at least better than that possessed by rivals), durable, generate returns which are appropriable, and they are (or should be) inimitable. The uniqueness of such traits leads to heterogeneity of firms (i.e. asymmetries in the production efficiencies), and the different levels of performance are the result of the different value created for consumers. Since competitive advantages are typically durable and competencies difficult to imitate, superior performance tend to persist over long periods of time (Teece et al., 1997; Geroski, 2002).

Notwithstanding this, empirics do fully reconcile with the expectations. Many studies have analyzed the structure in the process of growth, conventionally by looking at the autocorrelation of growth rates over time (under different autoregressive lags); even though ideally the time series should be long enough to estimate unbiased parameters, positive values imply that growth process goes beyond the randomic case and displays memory.[1] The evidence is quite mixed and highly dependent on the sample (e.g. country and sector peculiarities), the measure of size, and the statistical methodolgy.[2] Results ranges from the presence of strong autocorrelation in the growth path as in Bottazzi et al. (2001) to the claim that firm growth can be approximated to a random walk process (Geroski, 2002).

On the other hand, scholars agree on the fact that our economy is populated by some persistently growing firms (and a handful of persistently high-growing ones) but the factors underlying such sustained growth still remains largely a black box. Some authors have even suggested that the presence of persistent superior performance, when referring to disproportionately higher profits, might be the simple result of fortune (Barney, 1986). The industrial economic literature is indeed underdeveloped in this respect and the few existing studies, mainly focused on high-growth units, aim to sketch merely a demographic profile of persistently growing companies (Coad, 2007; Coad and Hölzl, 2009; Capasso et al., 2013). Typically, larger and older firms are those who achieve more persistent and smoother growth dynamics, while small firms tend to be characterized by more erratic patterns.

2.3 Connecting persistence of innovation to persistence of growth

We do not know of previous attempts linking other economic or financial factors to persistent growth behaviour. To search for the suitable candidates we need to do a step back and refer more closely to the literature investigating the determinants of firm growth. Among the possible

[1] More recently scholars have started exploiting quantile autoregression techniques to take into consideration the entire distribution of the growth rates. This allows to verify whether some degree of persistence is detected in the full spectrum of growth events rather than on the "average" firm.

[2] We do not report here an exaustive discussion on the previous evidence as it goes beyond the purpose of this paper.

explanations for asymmetries in firm performance, the ability to innovate and the production efficiencies are certainly the core drivers. In particular, if markets operate as efficient selectors, firms featured by good innovative capabilities and/or high production efficiency should grow and gain market shares at the expenses of less innovative and efficient competitors. Likewise, as such innovative capabilities have been proved to be persistent over time, persistently higher innovative capabilities should translate into persistently higher firm performance, profitability and growth in primis (Dosi and Nelson, 2010).

This background helps us to formulate some conjectures on the effects that persistence of innovation may play on persistence of corporate growth. Indeed, as innovation success is likely to be the result of a systematic engagement into innovation activities, we expect firms who are able to persistently translate their innovative efforts into valuable outcomes to overcome their competitors continuously for longer periods, put differently, to show a higher degree of persistence in their growth paths. Since the innovation process involves uncertainty and risk taking, it is characterize by degrees of complexity, uncertainty and idiosyncrasy, investing for innovation is however a necessary but not sufficient condition to succeed. Thus we expect that persistence in R&D investments does not necessarily spur persistent growth.

3 Data and empirical setting

In this Section we present our data, define the main variables and introduce the empirical methodology that we exploit to test whether persistence of innovation spurs persistence of growth.

3.1 Source and variables

We draw upon firm-level data from the Survey on Business Strategies (Encuesta Sobre Estrategias Empresariales, henceforth ESEE) which has been conducted yearly since 1990 by the SEPI foundation, on behalf of the Spanish Ministry of Industry. This annual survey gathers extensive information on around 2000 manufacturing companies operating in Spain and employing at least ten workers. The sampling procedure ensures representativeness for each two-digit NACE-CLIO[3] manufacturing sector, following both exhaustive and random sampling criteria. More in detail, in the first year of the survey all Spanish manufacturing firms employing more than 200 workers were required to participate (715 in 1990) and a sample of firms employing between 10 and 200 workers were selected by stratified sampling (stratification across 20 manufacturing sectors and four size intervals) with a random start (1473 firms in 1990). In order to guarantee a high level of representativeness, all newly created companies with more than 200 employees (rate of response around 60%) together with a random sample of firms with fewer than 200 workers and more than 10 (rate of response around 4%) have been incorporated in the survey every year.

In this paper, we refer to data that were obtained between 1990 and 2009, restricting our analysis on a sample of 331 continuing incumbent firms observed for 20 years (6,620 observations). The survival bias that the balancing procedure might possibly introduce is minimal in this case as we will run a comparative analysis across different groups of surviving firms.

We measure firm growth in terms of total sales (henceforth GRS). This is defined as the log-difference:

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

[3]NACE is the usual industrial classification of economic activities within the European Union while CLIO is the nomenclature used by the Spanish inputoutput tables. The Spanish Accounting Economic System (National Institute of Statistics:http://www.ine.es/) officially recognises both classifications.

where

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

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

Innovation performance are measured by using two conventional and widely adopted input and output indicators, namely R&D-to-sales intensity (total R&D expenditure over total turnover, henceforth RDI) and the number of patent applications (PAT). Beside demographic characteristics such as age, size (proxied by number of employees) and industry affiliation (2-digit)[4] we consider and introduce in our analysis a set of control variables which might influence the pattern of growth: a standard labour productivity index computed as the ratio between value added and number of employees (LP), the export intensity computed as the ratio between sales to foreign markets and total sales (EXPI), and a measure of financial leverage computed as percentage which represent the stockholders' equity on total liabilities (EQ/DEBT).

3.2 Measuring persistence of growth and innovation

As the data are recorded on annual basis, our measure of persistence of growth performance is a "growth spell" measured as the number of successive years in which a firm shows positive growth rates (as defined above). Thus a growth spell is considered as starting in year t if the firm did not growth in $t-1$, and analogously the spell will end in year T when a firm stops growing, after one or more consecutive years of positive growth performance.

Growth ≤ 0	Growth > 0	Growth > 0	Growth > 0	Growth > 0	Growth ≤ 0
t-1	t	t+1	t+2	T	T+1

Figure 1: A growth spell of four years

As already stressed, we want to uncover what factors are positively related to the probability and the length of growth spells, in other words what determines persistence in sales growth. We pointed out in Section 2 that our main concern is to verify if, and to what extent, a systematic engagement in innovation activities, as well as persistent innovation success, is conntected to longer periods of sustainable expansion. Notice that a problem of endogeneity might arise if one considered the "innovation status" precisely during the growth spell, as the former is likely to be pre-determined by the latter and reverse causality issues may be relevant. A very similar problem was detected in the influencial paper by Geroski et al. (1997), studying how the persistence of innovation varies according to the intensity of patenting. Interestingly, they solved the issue looking for the relationship between the number of innovations produced by a firm just prior to an innovation spell and the length of the spell that follows. We borrow their strategy and we rearrange it in line with our framework.

Therefore we define the innovation status at the beginning of each growth spell on the basis of the frequency with which a firm has shown positive R&D expenditure or applied for patents in a time window of five years prior the growth spell (see Figure 2).

[4]We will consider a broad distinction between high-tech (HT) and low-tech (LT) industries according to the Eurostat classification.

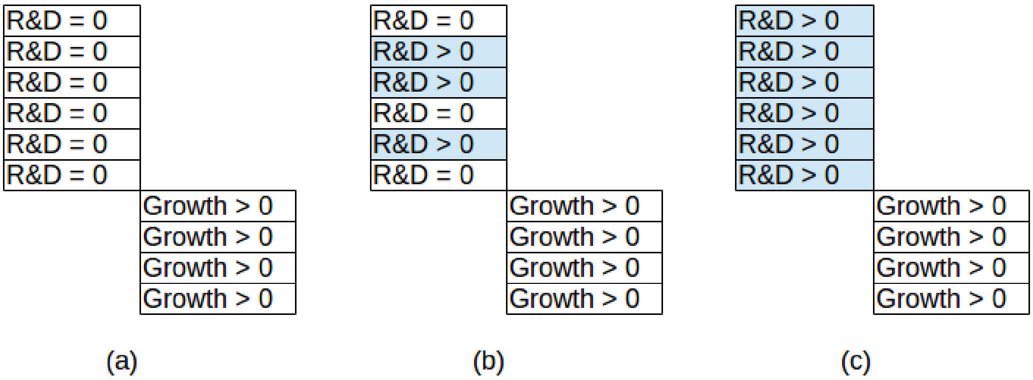

Figure 2: Definition of the innovation status based on R&D expenditures: NOI, OI, PI (definition based on patent applications is analogous). These figures represent an example of growth spell of four years and the R&D status defined in the time window of five years pre-spell. Panel(a): firms who never invested in R&D and classified as NOI. Panel(b): firms who occasionally invested in R&D and classified as OI. Panel(c): firms who persistently invested in R&D and classified as PI.

Subsequently, we define three distinct categories, namely: (i) non-innovators (NOI), as those firms that have never invested in R&D, or alternatively never applied for a patent in the time window considered, (ii) occasional innovators (OI), as those firms that exhibit a discontinuos and irregular innovation behaviour, and (iii) persistent innovators (PI), as those firms that have continuously, year after year, spent for R&D or applied for patents. Notice that our classification leads to three mutually exclusive dummy variables.

The choice of considering the behaviour pre-growth spell, as already highlighted, is aimed to reduce the possible endogeneity. More subjective is the choice of building a time window of five years, as well as to build an innovation status collapsing the information into three categories only. Our criterion balances between the aim at capturing a reasonably long number of years and a reasonable time lag through which innovation may affect growth. Anyhow, we have checked the our findings are not driven by the specific definitions that we impose to our data (see Section 4.3 for details).

3.3 Empirical methodology

The empirical setting we choose to model the degree of duration dependence in the growth path is well known and it is based on survival methods. In a nutshell, we take the spell of time in which a firm grows as unit of analysis, and model the probability that the spell will end at any particular time.

The primary goal of our multivariate analysis is to assess the effect of the innovation status (i.e. non-innovator, occasional innovator, persistent innovator) on the hazard of growth spell ending, while controlling for a large set of additional variables which take into account other micro and macro-level features that might also influence a firm's growth pattern. To this end we adopt a discrete time proportional hazard model with gamma mixture distribution to summarize unobserved individual heterogeneity (also said "frailty"), as proposed by Meyer (1990).[5]

The methodology consists of estimating a discrete time representation of the underlying continuous time proportional hazard function, parameterized as follows:

[5]The choice of implementing a discrete rather than a continuous time approach is motivated by the nature of our data. Indeed, even if growth transitions occured during the year, we record data only on annual basis.

$$\lambda_i(t) = \theta_i \lambda_0(t) \exp\{z_i(t)'\beta\} \tag{3}$$

where $\lambda_i(t)$ is the hazard function, $\lambda_0(t)$ is the baseline hazard at time t (an arbitrary non-negative function of t), $z_i(t)$ is a vector of fixed or time-varying explanatory variables (covariates) for firm i, and β is a vector of parameters. Finally, θ_i is a random variable that is assumed to be independent of $z_i(t)$, and represents the frailty which is incorporated multiplicatively.[6]

Following the approach introduced by Prentice and Gloeckler (1978) one can assume that the discrete hazard is given by a complementary log logistic (*cloglog* function), hence obtaining a discrete time counterpart of the underlying countinuous time proportional hazard of equation 3, that is:

$$\lambda_i(t) = 1 - \exp\{-\exp(z_i(t)'\beta + \lambda_0(t)) + \theta_i\} \tag{4}$$

To estimate the model of equation 4 the unit of analysis must be the growth spell, therefore the dataset must be re-organised so that, for each firm, there are as many data rows as there are time intervals at risk of the event occurring. In practical terms our dependent variable will be a simple binary indicator taking value zero for the survival period (positive growth rate), and one when the growth spell ends (what we previously denoted as period T, see Figure 1). We choose the natural logarithm of time ($\ln(t)$) as baseline hazard function to accounts for the risk of spell ending exclusively attributed to the passage of survival time.[7] It might be the case that some growth spells are in operation before the first year used for the analysis or in the last year of observation, a problem known respectively as left or right censuring. To account for this issue, we carefully include in our model two control variables for left-censored and right-censored spells.

The model is estimated separately to study the effect of persistence in R&D engagement and persistence of patenting. For both exercises we produce several specifications with the aim of assessing the reliability of the estimates: we include step-by-step a wide set of control variables based on the theoretical background put forward in Section 2. The first specification – Model(1) – looks only at the effect of the innovation status, based on R&D or patent applications, on growth spell. The second specification – Model(2) – mimics the first but it allows for dummies to accurately control for censuring. In the third – Model(3) – we include basic demographic features, in particular the age and the size of the firm along with its industry affiliation.[8] The last specification – Model(4) – contains the full set of covariates, so that an accurate control for the efficiency, export propensity, ongoing investments in R&D activities and financial status is take into account.

4 Results

4.1 Descriptive evidence

Before moving to the econometric analysis, in this Section, we provide descriptive statistics on our working sample and some preliminary univariate evidence regarding the role of

[6]In principle, any continuous distribution with positive support, mean one and finite variance, can be employed to represent the frailty distribution. However, the gamma distribution gives a closed form expression for the likelihood function, avoiding numerical integration and problems of convergence (Meyer, 1990).

[7]To check whether our findings were influenced by the choice of the baseline hazard, we re-estimated the model of equation 4 using a flexible high-order polynomial in survival time. We tested both quadratic and cubic polynomial specifications; results were in line with those presented in this document.

[8]We broadly distinguish between high-tech and low-tech industries according to the Eurostat taxonomy. Indeed the computational burden of the estimation did not allow us to include a full set of industry dummies as the converenge of the likelihood maximization was impossible to achieve.

Table 1: Distribution of sales growth spell lengths and maximum spell lengths by firms

Lenght years	All spells		Maximum spells	
	No.	%	No.	%
1	825	50.77	4	1.21
2	458	28.18	83	25.08
3	182	11.20	113	34.14
4	76	4.68	56	16.92
5	53	3.26	47	14.20
6	21	1.29	18	5.44
7	4	0.25	4	1.21
8	3	0.18	3	0.91
9	2	0.12	2	0.60
10	1	0.06	1	0.30
Total	1,625	100.00	331	100.00

persistence of innovation on persistence of growth performance.

Table 1 presents the distribution of growth spell lengths and maximum spell lengths. As expected, the number of spells is much greater than the number of firms, denoting that some firms have more than one spell. However, as can be seen, this dissimilarity is mostly accounted for by spell lengths of 1 years, which represent the 50% of the total numbers of spells. On the other hand, for spell lengths of 7 years or more, the total number of spells is exactly equal to the number of firms that have maximum duration spells of that length. Finally, it is worth nothing that, although we track firms over a period of 20 years, the maximum length of the spells is ten years. This evidence reinforces the idea that persistent growth is a rare phenomenon.

Tables 2 and 3 show basic statistics of the main variables broken down by each innovation status. A first comment on the size of each subsample is in order: as expected, the largest groups are non-innovators, both in terms of R&D and patent applications; the group of occasional innovators based on R&D expenditure is similar in number to the one of persistent innovators, whereas we do observe that only a handful of firms persistently engage in patenting activities.[9] We can see some sharp differences among firms belonging to different innovation statuses: indeed, PI are older and larger than their counterparts, they are more R&D intensive, more efficient, export oriented and predominantly operating in high-tech industries. On the other hand we do not observe any profound difference in terms of growth potential or financial status. To notice that the same characterization is valid for OI with respect to NOI.

As preliminary evidence, we estimate Kaplan-Meier survival functions for the sample of persistent innovator vs. all the other firms (non and occasional innovators) and present them in Figure 3. This univariate analysis suggests that persistent innovators enjoy longer growth spells than "sporadic" innovators (indeed the survival function of former is always above that one of the latter). In addition, the difference is particular sizeable when innovation is measured in terms patenting activity.

[9] Although this evidence was expected, to check whether our results were influenced by the too small sub-sample size we replicate the analyses by using a continuous variable (instead of collapsing the information into three dummies) that ranges from 0 to the lenght of the time window pre-spell, depending on the frequency with which a firm undertake R&D activities or apply for patents. We elaborate more in depth this point and provide robustness checks in Section 4.3.

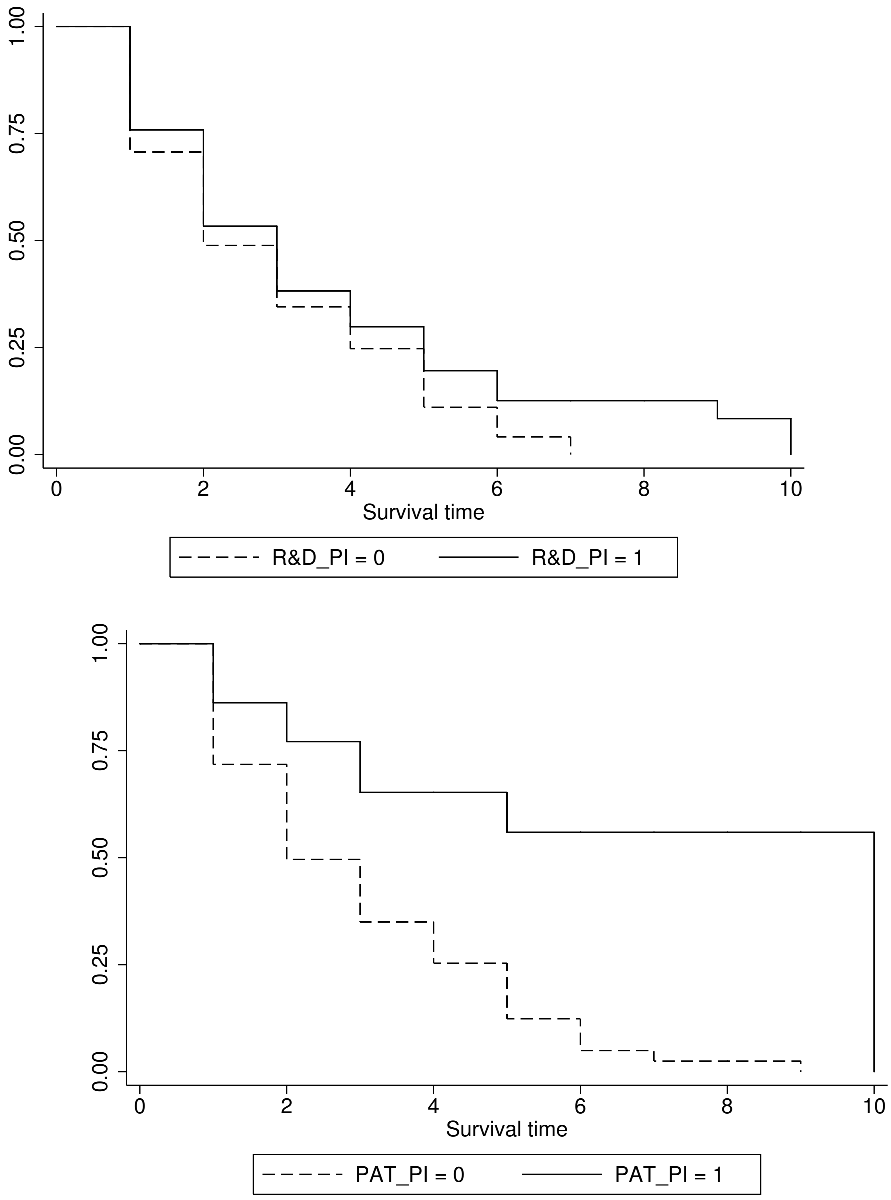

Figure 3: Kaplan-Mayer survival function (PI based on 5 years pre-growth spell). Upper panel: R&D measure. Bottom panel: Patent applications measure

Table 2: Descriptive statistics broken down by innovation status (R&D)

	Mean	Std.Dev.	Median	Min	Max
NOI (1,241 obs):					
GRS	0.16	0.18	0.12	0.00	1.93
ln(AGE)	3.28	0.45	3.26	2.08	4.71
ln(SIZE)	3.44	1.00	3.22	1.61	7.34
RDI	0.00	0.00	0.00	0.00	0.09
ln(LP)	3.48	0.55	3.46	1.03	5.57
EQ/DEBT	0.05	0.02	0.05	0.00	0.10
EXPI	0.08	0.17	0.00	0.00	1.00
HT	0.12	0.32	0.00	0.00	1.00
OI (533 obs):					
GRS	0.19	0.22	0.13	0.00	1.91
ln(AGE)	3.33	0.55	3.30	1.79	4.71
ln(SIZE)	4.30	1.25	3.91	2.20	8.99
RDI	0.01	0.02	0.00	0.00	0.27
ln(LP)	3.79	0.68	3.69	0.59	6.62
EQ/DEBT	0.05	0.02	0.05	0.00	0.09
EXPI	0.25	0.30	0.10	0.00	1.00
HT	0.14	0.34	0.00	0.00	1.00
PI (588 obs):					
GRS	0.17	0.21	0.11	0.00	2.37
ln(AGE)	3.62	0.54	3.64	2.08	4.76
ln(SIZE)	5.43	1.29	5.51	2.30	8.95
RDI	0.02	0.03	0.01	0.00	0.26
ln(LP)	3.90	0.52	3.86	0.81	6.31
EQ/DEBT	0.05	0.02	0.05	0.00	0.09
EXPI	0.39	0.30	0.35	0.00	1.00
HT	0.31	0.46	0.00	0.00	1.00

4.2 Main evidence

To complement the preliminary evidence, in this Section, we turn to estimates of the discrete time proportional hazard model with gamma frailty and discuss the main findings on the determinants of hazard rates. Table 4 and 5 report results of four econometric specifications to test, respectively, the effect of persistence of R&D engagement and persistence of patenting on the duration of the growth spell. As our criterion to define the innovation status leads to three mutually exclusive categories, we select the non-innovative firms (R&D_NOI or PAT_NOI) as benchmark group so that estimated coefficients for the other two groups readily represent the effect of being occasional or persistent innovator relative to the reference.

For the sake of comprehension, estimated coefficients portray the effect of covariates on the hazard of ending a growth spell. Thus negative (positive) coefficients are interpreted as a descrese (increase) in the hazard rate, or more easily, an increase (decrease) in the expected duration of the growth spell.

Looking at the overall evidence shown in Table 4 we can conclude that persistence of R&D investments plays only a very weak role on persistence of sales growth. In the baseline model – Column(1) – we obtain a negative and statistical significant coefficient for R&D_PI, pointing to a degree of association between the persistence of R&D activities and the length of subsequent growth spells. The lack of significance for R&D_OI indicates that firms who occasionally undertake R&D do not differ in terms of persistence of growth from firms that do not invest in R&D at all.[10] The inclusion of censoring dummies in Column(2) slightly changes the magnitudes of

[10] A simple t-test allows to assess whether the coefficients for occasional and persistent innovators statistically differ. They actually do, with p-value<0.001.

Table 3: Descriptive statistics broken down by innovation status (patent applications)

	Mean	Std.Dev.	Median	Min	Max
NOI (1,980 obs):					
GRS	0.17	0.19	0.12	0.00	1.93
ln(AGE)	3.35	0.50	3.33	1.79	4.75
ln(SIZE)	3.98	1.31	3.61	1.61	8.95
RDI	0.01	0.02	0.00	0.00	0.27
ln(LP)	3.62	0.60	3.60	0.59	6.62
EQ/DEBT	0.05	0.02	0.05	0.00	0.10
EXPI	0.18	0.26	0.03	0.00	1.00
HT	0.16	0.36	0.00	0.00	1.00
OI (353 obs):					
GRS	0.17	0.21	0.12	0.00	2.37
ln(AGE)	3.45	0.54	3.47	2.08	4.76
ln(SIZE)	4.81	1.64	4.74	1.61	8.99
RDI	0.01	0.03	0.00	0.00	0.26
ln(LP)	3.77	0.59	3.78	1.78	6.31
EQ/DEBT	0.05	0.02	0.04	0.00	0.09
EXPI	0.32	0.33	0.19	0.00	0.98
HT	0.20	0.40	0.00	0.00	1.00
PI (29 obs):					
GRS	0.09	0.06	0.07	0.00	0.24
ln(AGE)	4.19	0.37	4.28	3.26	4.65
ln(SIZE)	5.94	0.71	5.97	4.34	7.40
RDI	0.06	0.05	0.03	0.00	0.14
ln(LP)	4.24	0.48	4.33	3.24	4.93
EQ/DEBT	0.06	0.01	0.05	0.04	0.08
EXPI	0.22	0.21	0.15	0.02	0.80
HT	0.52	0.51	1.00	0.00	1.00

the coefficients but do not alter their significance. However, once basic demographic controls are added to the model, the pattern previously identified vanishes and the conclusion we derive is that the duration of the growth spell is fully independent from the innovation status defined at the commence of the spell. Specification in Column(4) confirms this evidence, but we recover an association (although significant only at 10% level) between size and growth spell duration. The negative coefficient for size suggests that larger firms have a higher tendency to experience longer periods of persistent sales expansion. Interestingly, none of the other potential determinats plays a role so that factors such as higher efficency as well as sounder financial conditions seem not to favour sustained growth patterns.

Results on innovation stutus proxied by patent applications are instead very stable (see Table 5) and, in line with our conjectures, point to a positive association between persistence of patenting and persistence of sales growth. The baseline specification – Column(1) – indicates that occasional innovators enjoy longer growth spells compared to non-innovators but persistent innovators are those actors who experience the longest period of sustained positive sales growth. The difference in magnitude of the estimated coefficients, so as the statistical signicance, for PAT_OI and PAT_PI is indeed vary sharp. Again, a simple t-test tells us that the coefficients for PI is statistically larger than that for OI (p-value<0.001). The scenario doesn not change when we examine the estimates for the alternative econometric specifications, and a common feature of the regressions shown in Column(3) and (4) is a size effect similar to the one discussed above (here the statistical significance is definitely stronger). Still, all the other explanatory variables do not exert any effect.

All these evidences confirm the conjectures that we put forward in Section 2, pointing to the following interpretation: *while engagement in innovation activities may lead to longer spells of growth, it does so only when firms (i) translate their innovative efforts into valuable outcomes and (ii) produce such outcomes persistently, year after year, over time.* Our results suggest that market competition erodes very quickly the competitive advantages that firms build upon their innovation success, at least if one assume that such advantages get reflected into gain of market shares. Therefore, structural competitive advantages come to the cost of being able to persistently overcome competitors in terms of higher innovation differentials. Not coincidentally it emerges a weak association between occasional innovation success and duration of growth spell.

Table 4: Estimates for the Proportional Hazard Model - R&D

	(1)	(2)	(3)	(4)
R&D_NOI	ref	ref	ref	ref
R&D_OI	0.0345	-0.1116	0.0174	0.0727
	(0.190)	(0.192)	(0.196)	(0.213)
R&D_PI	-0.5860***	-0.4633**	-0.2151	-0.1055
	(0.210)	(0.206)	(0.240)	(0.278)
ln(AGE)			-0.0005	0.0628
			(0.153)	(0.157)
ln(SIZE)			-0.1121	-0.1379*
			(0.071)	(0.082)
RDI				1.3181
				(3.964)
ln(LP)				-0.0951
				(0.146)
EXPI				0.0838
				(0.358)
EQ/DEBT				1.7779
				(3.664)
HT			0.0884	-0.0563
			(0.227)	(0.245)
ln(t)	3.4823***	3.5424***	3.2798***	3.1504***
	(0.319)	(0.337)	(0.319)	(0.340)
Censoring dummies	no	yes	yes	yes
Year dummies	yes	yes	yes	yes
Testing frailty:				
LR test on Gamma var.	1688.92***	1580.03***	1551.75***	1526.84***
Log likelihood	-653.01	-650.31	-660.93	-641.04
Obs	2362	2362	2359	2171

Notes: Coefficient estimates of regression from different specifications of model (4), taking non-innovators as the baseline category. The improvement in log-likelihood relative to the no-frailty model is deteced with a standard likelihood-ratio test (LR). Standard errors in parenthesis: ***, ** and * indicate significance at 1%, 5% and 10% level, respectively.

4.3 Robustness check

In this Section we report a series of additional exercises we carried out to assess whether our findings were invariant to alternative definitions of innovation status.

Table 5: Estimates for the Proportional Hazard Model - Patent applications

	(1)	(2)	(3)	(4)
PAT_NOI	ref	ref	ref	ref
PAT_OI	-0.3671*	-0.3627*	-0.3995*	-0.3920*
	(0.208)	(0.206)	(0.218)	(0.221)
PAT_PI	-3.2918***	-3.2484***	-3.0772***	-3.2300***
	(1.037)	(1.028)	(1.077)	(1.232)
ln(AGE)			0.0349	0.0628
			(0.152)	(0.149)
ln(SIZE)			-0.1381**	-0.1600**
			(0.062)	(0.072)
RDI				2.9219
				(3.575)
ln(LP)				-0.1466
				(0.135)
EXPI				0.2693
				(0.327)
EQ/DEBT				1.1568
				(3.405)
HT			0.0019	-0.0380
			(0.218)	(0.227)
ln(t)	3.2227***	3.1869***	3.2423***	2.9341***
	(0.303)	(0.311)	(0.330)	(0.338)
Censoring dummies	no	yes	yes	yes
Year dummies	yes	yes	yes	yes
Testing frailty:				
LR test on Gamma var.	1674.63***	1557.43***	1563.23***	1512.87***
Log likelihood	-656.25	-658.82	-652.48	-645.79
Obs	2362	2362	2359	2171

Notes: Coefficient estimates of regression from different specifications of model (4), taking non-innovators as the baseline category. The improvement in log-likelihood relative to the no-frailty model is deteced with a standard likelihood-ratio test (LR). Standard errors in parenthesis: ***, ** and * indicate significance at 1%, 5% and 10% level, respectively.

A first natural extension we propose consists of changing the length of the time window pre-spell along which the three categories (NOI, OI, PI) are defined. In this respect we choose a shorter window of four years and a longer window of six years, and for both cases, the three groups are created according to the original criterion (see Figure 2). Thus persistent innovators are still those firms who continuously, year after year, invest in R&D or apply for patents over the new time windows.

A second extension regards the nature of the variable defining the innovation status. Indeed one might argue that collapsing all the information into three dummies might not be the best choice, as for example firms who innovate one out of five years pre-spell of growth have been treated as firms that innovate for four out of five periods pre-spell. Hence we define two new continuous variables (R&D_PERS and PAT_PERS) whose ranges go from 0 to the lenght of the time window pre-spell, depending on the frequency with which a firm undertake R&D activities or apply for patents, respectively.

Tables 6 and 7 show the estimates for the model with the full set of covariates. The story we deliver is in line with to the one proposed in Section 4: we confirm the lack of association between persistence of R&D expenditure and persistence of sales growth – see Column(1) – whereas we still can claim that persistent innovators, when innovation outcome is proxied by patent applications, display the highest propensity to experience longer spells of growth – see Columns(2).[11] As shown in Column(3) and (4) this result holds also when we estimate the model including the continuous variables which alternatively define the innovation status of firms.

A final extension aims to take into account two characteristics of technological knowledge, namely cumulability and non-exhaustibility (David, 1992). Both features could have implications in our framework, as the generation of new knowledge is typically conditioned upon the existing stock that can be used as an input because of its non-exhaustibility. Thus, instead of defining the innovation status of each firm in a finite time window pre-growth spell, we want to trace the innovation behaviour of the firm from the first year of observation up the beginning of the spell, put it differently we want to account for the full innovation history pre-spell. This task can be easily accomplished by removing the threshold of the window prior the spell where the innovation status was defined, and simply defining two continuous variables (R&D_PERS_FULLH and PAT_PERS_FULLH) that represent the number of years in which a firm has engaged in R&D activities or applied for patents. Results are shown in Table 8 and, on the whole, we can still confirm our main findings.

5 Conclusions

In this work we have explored the link between the degree of persistence of innovation activities and the persistence of growth performance, using both input and output proxies to characterize the innovation status of firms.

Although there are many studies linking firm growth to micro and macro-level variables, the literature targeting the determinants of persistent growth is only of recent development and the underlying factors shaping and limiting this growth behaviour are still largely unknown. This is, however, a topic that should deserve much more attention and contributions. Indeed, if one role out that persistent superior performance occur at random (and this might be per se an interesting research question), this kind of growth behaviour may be considered as a tangible proof of competetive advantages at work: firms who possess better operating capabili-

[11] Although in the main results shown in Table 5 the coefficient for PAT_OI was barely significant, now we loose such significance. In a way we can state that firms who sporadically patent their innovations do not differ in terms of persistence of growth performance from firms who do not patent at all.

Table 6: Estimates for the Proportional Hazard Model - innovation status defined on a time window of 4 years pre-growth spell

	(1)	(2)	(3)	(4)
R&D_NOI	ref			
R&D_OI	-0.2478			
	(0.242)			
R&D_PI	-0.0212			
	(0.292)			
PAT_NOI		ref		
PAT_OI		0.0229		
		(0.251)		
PAT_PI		-3.5172**		
		(1.368)		
R&D_PERS			-0.0383	
			(0.069)	
PAT_PERS				-0.3655***
				(0.135)
ln(AGE)	0.1944	-0.0187	0.0055	0.0093
	(0.174)	(0.162)	(0.160)	(0.156)
ln(SIZE)	-0.1574*	-0.1573*	-0.1230	-0.1630**
	(0.089)	(0.081)	(0.086)	(0.078)
RDI	1.6887	3.0875	0.1829	2.6069
	(4.391)	(3.886)	(4.281)	(3.832)
ln(LP)	-0.0171	-0.1892	-0.1102	-0.1038
	(0.161)	(0.153)	(0.153)	(0.149)
EXPI	0.0106	0.1804	0.2604	0.3164
	(0.390)	(0.367)	(0.371)	(0.351)
EQ/DEBT	5.5726	6.6153*	5.4036	4.4876
	(3.959)	(3.860)	(3.821)	(3.682)
HT	-0.2630	-0.0987	-0.0903	-0.1398
	(0.267)	(0.256)	(0.253)	(0.245)
ln(t)	3.6364***	3.5854***	3.4157***	3.3663***
	(0.373)	(0.359)	(0.341)	(0.334)
Testing frailty:				
LR test on Gamma var.	1683.17***	1685.19***	1664.60***	1658.03***
Log likelihood	-629.08	-626.33	-638.75	-640.18
Obs	2269	2269	2269	2269

Notes: Standard errors in parenthesis: ***, ** and * indicate significance at 1%, 5% and 10% level, respectively. Columns (1) and (2) report estimates of the innovation status (NOI, OI, PI) defined on a time window of 4 years pre-growth spell. Columns (3) and (4) report estimates of the continuous version of the innovation status, still defined on a time window of 4 years pre-growth spell. The improvement in log-likelihood relative to the no-frailty model is deteced with a standard likelihood-ratio test (LR).

Table 7: Estimates for the Proportional Hazard Model - innovation status defined on a time window of 6 years pre-growth spell

	(1)	(2)	(3)	(4)
R&D_NOI	ref			
R&D_OI	-0.0407			
	(0.201)			
R&D_PI	-0.0188			
	(0.274)			
PAT_NOI		ref		
PAT_OI		-0.1810		
		(0.210)		
PAT_PI		-2.8346**		
		(1.282)		
R&D_PERS			-0.0050	
			(0.043)	
PAT_PERS				-0.2507***
				(0.092)
ln(AGE)	0.2068	0.2108	0.1883	0.1102
	(0.162)	(0.156)	(0.158)	(0.156)
ln(SIZE)	-0.1763**	-0.1415**	-0.1851**	-0.1181
	(0.080)	(0.070)	(0.077)	(0.072)
RDI	0.8007	2.2462	1.2139	2.5166
	(3.858)	(3.496)	(3.733)	(3.591)
ln(LP)	-0.1634	-0.1002	-0.0582	-0.0519
	(0.138)	(0.133)	(0.137)	(0.139)
EXPI	0.4606	0.3195	0.3420	0.2651
	(0.340)	(0.320)	(0.336)	(0.334)
EQ/DEBT	1.4203	-0.5772	-2.1584	0.5456
	(3.590)	(3.432)	(3.483)	(3.541)
HT	-0.0355	-0.0355	-0.0374	-0.1449
	(0.239)	(0.229)	(0.232)	(0.234)
ln(t)	2.8591***	2.6459***	2.6936***	2.7851***
	(0.330)	(0.347)	(0.322)	(0.352)
Testing frailty:				
LR test on Gamma var.	1279.08***	1278.99***	1256.61***	1283.46***
Log likelihood	-646.42	-645.61	-658.37	-643.08
Obs	1977	1977	1977	1977

Notes: Standard errors in parenthesis: ***, ** and * indicate significance at 1%, 5% and 10% level, respectively. Columns (1) and (2) report estimates of the innovation status (NOI, OI, PI) defined on a time window of 6 years pre-growth spell. Columns (3) and (4) report estimates of the continuous version of the innovation status, still defined on a time window of 6 years pre-growth spell. The improvement in log-likelihood relative to the no-frailty model is deteced with a standard likelihood-ratio test (LR).

Table 8: Proportional Hazard Model - definitions based on full history

	(1)	(2)	(3)	(4)
R&D_PERS_FULLH	-0.0377*	-0.0049		
	(0.022)	(0.025)		
PAT_PERS_FULLH			-0.1253**	-0.1368**
			(0.050)	(0.057)
ln(AGE)	0.0355	0.1466	0.0704	0.1452
	(0.161)	(0.167)	(0.155)	(0.163)
ln(SIZE)	-0.0266	-0.1395	-0.0828	-0.1248
	(0.086)	(0.094)	(0.076)	(0.088)
RDI		-0.4433		-1.2409
		(4.728)		(4.540)
ln(LP)		-0.1965		-0.1019
		(0.167)		(0.166)
EXPI		0.1477		0.2287
		(0.411)		(0.391)
EQ/DEBT		-2.5127		3.8987
		(4.033)		(4.018)
HT	0.2161	0.1306	0.1585	0.2619
	(0.271)	(0.284)	(0.268)	(0.278)
ln(t)	4.6466***	4.3874***	4.5542***	4.1873***
	(0.430)	(0.415)	(0.430)	(0.397)
Testing frailty:				
LR test on Gamma var.	2447.88***	2349.45***	2442.79***	2361.42***
Log likelihood	-678.96	-667.69	-677.77	-658.71
Obs	3059	2831	3059	2831

Notes: Standard errors in parenthesis: ***, ** and * indicate significance at 1%, 5% and 10% level, respectively.

ties and persistenlty higher innovation differentials, defeat competitors and gain market shares repeatedly over time.

Unfortunately previous contributions are limited to provide a mere demographic characterization of persistently growing units, and little consensus exists on the strategies that companies can adopt to maintain desired growth rates. Motivated by the theoretical background we focus on innovation as core driver of growth and, more precisely, we test whether persistence of innovation spurs, to some extent, persistence of growth.

We carried out an empirical investigation on a long and rich panel of Spanish firms comprising micro-level information and frame our analyses considering different indicators of innovation in order to appreciate differentiated patterns. Our results suggest, in a rather robust fashion, that periods of sustained sales expansion are, on average, anticipated by persistent innovation success. While this systematic success allows some firms to build durable competitive advantages, it is not the case for firms who occasionally translate their innovative efforts into innovative outcomes. Moreover, we do find that persistence in R&D investments is not enough to inject structure in the growth process.

Although we believe that our study provides novel insights to the industrial economic literature, it obviously suffers of some limitations that might be object of further investigations. A first extension might be to carefully account for entry and exit phenomena. Although some difficulties may arise in defining when firms do actually fail and exit the market, the growth dynamics of nascent enterprises who are typically the recepee of subsidies for innovation might be of particular concern for policy making.

Secondly, we have to admit that we are fully silent with respect to factors of more direct derivation from management research; we do recognize that such factors are likely to influence the growth behaviour of firms. Among the possible extensions one may foreseee, we think that it would particularly relevant to look deeper into organizational traits, or exploring the role of differences in the underlying firm strategies and managerial characteristics. Are some growth strategies more effective than others? Or, are some organizational and governance structures more helpful to convert persistent innovation success into sustained growth than others? Answering these questions not only would complement our preliminary evidence but would also increase the overall understanding of some intricate firm-industry dynamics.

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