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On Firm Growth and Innovation: Some new empirical perspectives using French CIS (1992-2004)

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Abstract

The aim of this paper is to examine whether firms that innovate, experience higher rates of growth than firms that do not. Our analysis is based on different models and econometric methodologies applied to several waves the Community Innovation Surveys (CIS) for French industry, during 1992-2004. Our main findings are that innovative firms grow more than non-innovative ones. The estimation techniques give results that are quite robust to the effects of different types of innovation on firm growth. In particular, the quantile regression results show that the coefficient of innovation is higher for firms with the highest growth rates, a result that is robust to different measures of the dependent variable.

Key words: Innovation, process and product innovator, firm growth, CIS.

JEL classification: D22, L20, L60, O31, O33

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Introduction

A major argument supporting innovation policy is that more innovation generates more growth which promotes higher levels of employment and job creation. Innovation is viewed as a means by which new knowledge is transformed into economic growth. So the notion that innovation results in more growth is a commonly accepted rationale for implementing innovation policy in both Europe and America.

While the *theoretical literature* provides excellent explanations for why innovation is a determinant of firm growth, *empirical studies* find it more difficult to identify a strong link between them, and the process of firm growth and its relationship with innovation has for long intrigued economists. Following the pioneering work of Mansfield (1962), evolutionary economics has maintained that innovation is crucially important for firm growth. More recently, analysis of firm growth and innovation has gained momentum (Ernst, 2001, Coad and Rao, 2008, Corsino and Gabriele, 2010). However, investigation of this relationship is not straightforward, it is difficult also to find empirical regularities with respect to the type of innovation, innovation proxies and methodologies used in the empirical literature.

Thus, our main objective here is to explore this relation empirically using data from the Community Innovation Surveys (hereafter, CIS) of French firms during the period 1992 to 2004. We focus on a panel of 1,074 firms obtained by merging three waves of the CIS with the French annual enterprise survey from 1992. The CIS makes it possible to analyse the impact of different types of innovation (product versus process) on firm growth and to use both qualitative and quantitative proxies for innovation. For the empirical analysis, we adopt a Gibrat-like model and exploit different specifications and estimation techniques to check the consistency and robustness of our results.

Our findings confirm that innovation has a positive effect on the rate of firm growth. In particular, our results show that if the effects of product innovation and process innovation are disentangled, the relationship with firm growth remains strong and positive. We find also that innovation is of crucial importance for high-growth firms. Our results are robust to different specifications of growth dynamics.

The paper is organised as follows. Section 1 provides a survey of the literature and defines our research questions; Section 2 presents the data and variables used; Section 3 describes the methodology; Section 4 comments on the results; and Section 5 concludes the paper.

1. Survey of the literature and research questions

A natural starting point for an investigation of the determinants of firm growth is the well-known Gibrat's Law framework. The 'law of proportionate effects', proposed by Gibrat (1931), argues that the firm size distribution is highly skewed, presumably following a log-normal function. Gibrat's framework assumes that firm size follows 'random walk': there are no determining factors that explain differences in firm growth. It has been shown that the rates of growth of large and/or old firms are very often erratic and, consequently, unpredictable (see Geroski, 1999). This means, for instance, that for large firms, there is no deterministic impact of innovation activity on their growth. It has been acknowledged that Gibrat's Law cannot be considered a general law, but rather a dynamic rule that is valid for large and mature firms (Sutton, 1997). Thus, its validity cannot be taken for granted *ex ante* (Lotti, Santarelli and Vivarelli, 2009). There is a large recent literature that deals with the theoretical coherence and empirical relevance of Gibrat's Law (Cefis *et al.*, 2007; Coad, 2009). Suffice to say that Gibrat's law is at odds with most of the latest empirical studies on the existence and persistence of heterogeneity in firms, including in their performance (Colombelli and von Tunzelmann, 2010).² Bottazzi *et al.* (2011) discuss the properties of the growth rate distributions in French manufacturing industry data and find significant differences in firm sizes across industries.

Among the studies that deal explicitly with innovation/growth links at firm level, many are inspired by Mansfield (1962). Mansfield's work was the first rigorous empirical assessment of the complex relationship between growth and innovation at the firm level. Mansfield (1962: 1042) asks 'How much of an impact does a successful innovation have on a firm's growth rate?' He first observed that firms that had achieved significant innovations grew more rapidly, and at rates of average growth that were twice as fast as in other firms. He noted also that the estimated effect depended on the industry under consideration and argued that innovation has a bigger impact on the growth rates of small firms. Mansfield's paper, which deals with the 'processes of firm formation, growth and decline' (Mansfield, 1962: 1043), is the first empirical evolutionary approach to the determinants of firm growth. While many

² An exception is Del Monte and Papagni (2001). Based on a sample of 500 firms in the period 1989-1997 (drawn from the Mediocredito survey of Italian manufacturing) they confirm Gibrat's Law. They show that the growth rate of firms is positively correlated with their research intensity (considered as a proxy for firm innovation activity).

firms decline and exit – in some cases soon after entry - others grow, innovate and build a capital of basic competencies (or capabilities) necessary to survive and succeed. These positive links are confirmed by Scherer (1965), Mowery (1983), and Geroski and Machin (1992) and are the core of the evolutionary approach (Dosi, 2005; Nelson and Winter, 1982; Winter, 1984). Innovation is assumed to be ‘good’ for growth and survival, but only under certain conditions. Firms need to capture the value from innovation (Teece, 1986) and, in some sectors, to implement methods to improve performance (e.g. economies of scale or scope). Innovation creates firm advantage over competitors, which results in increased market share, the mechanism that transforms innovation into growth. Some authors argue that technical innovation promotes firm growth through a second (although less important) way. They argue that the process of technological innovation transforms the firm’s core competencies (Geroski *et al.*, 1993; Lee, 2010), making the firm more able to innovate and/or cope with the selection environment. In a sense, the study addresses the two faces of research and development (R&D): innovation and learning (an idea that stems from the famous analysis by Cohen and Levinthal, 1989).

A recent strand of studies on different types of firms provides new empirical insights into the effects of innovation on firm performance. For example, Audretsch (1995) looks at the post-entry performance of new firms. He proves that in industries where innovative activity is important, the probability of a new entrant surviving is lower than in industries where innovation is less important. He finds also that entrants that survive show higher growth rates.³ Cefis and Marsili (2005) examine the effects of innovation on survival using data on Dutch manufacturing firms. They show that firms benefit from an innovation premium that extends their life in the industry, independent of firm age or size. Process innovation seems to have a particularly distinctive effect on survival. Cainelli *et al.* (2006), using CIS data on Italian service sectors, confirm that innovation activities have a positive impact on firm growth and productivity. Coad and Rao (2008) use a large sample of high-tech firms and find that growth may or may not be related to innovation activity (as measured by firm patenting activity). They employ quantile regression techniques and note that innovation is more crucial for growth in ‘rapid-growth’ firms. Along the same lines, Cassia *et al.* (2009) and Cassia and Colombelli (2008) provide evidence that university knowledge inputs and outputs are important determinants of UK entrepreneurial firms’ growth. Ernst (2001), in his study of

³ Baldwin and Gellatly (2006) provide a rich analysis of an evolutionary approach, but deal only with small Canadian firms.

growth in German firms, conducts a quantitative analysis and finds that, after a lag of some two to three years following patent application to a specific patent system (national or European), sales increase. This would seem to underline that the effects of invention on a firm's growth performance are not immediate, but rather emerge soon after the invention has been implemented (note that mere application for a patent does not mean the invention is implemented). Corsino and Gabriele (2010) uses new (and unique) types of data. He gathered information on new semiconductor devices commercialised during the period of 1998-2004 from producers around the world. He carried out a corporate level econometric analysis and found that the most recent innovations have a more significant effect on firm growth. When he conducted the estimations at the business-unit level, the influence of product innovation on business-unit growth is higher than found at the corporate level. Therefore, he stresses the importance of the level of observation in trying to identify an association between growth and innovation.

This literature survey provides some general findings. The studies reviewed mostly provide evidence in favour of a positive and significant relation between firm innovation and firm growth. This finding is consistent across the use of different proxies for innovation. As a consequence, it is tempting to consider this finding a stylised fact. Only a few studies found results mitigating the relationship between innovation and growth.⁴ Of course, innovation is only one factor among several explanatory variables and there are some important issues that remain unaddressed or neglected by the current literature.⁵

First, the type of innovation (product versus process) is only infrequently taken account of in the literature. Some studies note that new products have an impact (Roper, 1997); others consider each type of innovation (Mansfield, 1962). Thus, it might be interesting to assess the effect of each type of innovation within the same framework. In this context, CIS data are useful in providing a great deal of information on the types of invention, and differentiate between product and process innovation. The paper by Mairesse and Mohnen (2010) demonstrated the richness of the data collected through the CIS.

Second, the literature uses different specifications for product and process innovation, and innovation proxies (R&D, patents). To cope with this problem, one of the original

⁴ E.g., Bottazzi et al. (2001), in a study of worldwide firms in the drug sector, find no relation between innovation and growth. These results would seem to be an exception, which might be due to the economic conditions in that sector.

⁵ Table 0 provides a summary of the main studies.

contributions of the present paper is that we use additional and complementary indicators based on CIS. This enables us to test the robustness of the innovation effect on growth by changing the definition of the innovation variables. For instance, we use qualitative as well as quantitative variables for innovation (e.g. share of innovative products and marginally modified products in turnover).

Also, Coad and Rao (2008) raise an interesting issue. They note that innovation is more crucial for ‘rapid-growth’ firms. Given this perspective, quantile regression is essential to test the effects of innovation on firms’ growth rates.

Finally, as some scholars have noted (in particular Geroski *et al.*, 1997), the specification of the dependent variable is important and may be crucial. Many studies seem not to attach much importance to their choice of index of performance, citing value-added rate of growth, sales growth, or other factors. This choice would seem to matter for testing the sensitivity of the results to the definition of the growth variable.⁶

In our view, these issues have been inadequately explored and documented in the literature dealing with the relation between innovation and firm growth, and summarized in Table 0, but should be considered critical for an accurate understanding of how this relation works. The present paper contributes to the literature by providing new means to deal with these issues. It focuses on French industry in the period 1992-2004. Our contribution lies in the use of different waves of the CIS for the French industries, and the application of different econometric methods to this research question. In particular, the use of quantile regression should capture the crucial important of innovation for high-growth firms.

INSERT TABLE 0 ABOUT HERE

2. Data description

This empirical study focuses mainly on the long-term, post-innovation growth performance of innovative firms, differentiated by type of innovation, compared with non-innovative firms. The sample used for the econometric analysis was constructed from CIS⁷ data and

⁶ Another difficult question that is not dealt with here, but warrants more attention is that the timing of the innovation effects (noted in particular by Mansfield, 1962 and Geroski and Machin, 1992) is extremely important for explaining the effects on growth (see Coad, 2007). Are these effects relevant in the short or medium/long term? Geroski and Machin (1992) show that the effects of innovation on firm performance are realised very soon after the firm innovates.

⁷ The CIS databank was made available to Naciba Haned under the mandatory condition of censorship of any individual information.

complemented by data from the 1992 annual enterprise survey.⁸ We obtained an unbalanced panel of 1,074 firms covering four time periods.⁹ Below, we discuss how we dealt with the data sources and sampling issues and describe sample and the variables derived.

2.1. Sources and sampling

Our analysis is based on a data set obtained from merging three waves of the CIS: CIS2 (1994-1996), CIS3 (1998-2000) and CIS4 (2002-2004). We collected information that enables us to construct variables measuring the firm growth rates over our study period, and their innovation activities during the same time period. We used CIS information on firm turnover, number of employees, and activity (identified with NACE codes).¹⁰ This information is available every second year, for each of three year time periods covered by the CIS. To capture innovation activity, the surveys include a set of questions asking whether the firm innovated or not in the three years prior to the survey. Thus, we can access information on product and process innovators for the periods 1994-1996, 1998-2000 and 2002-2004. We merged the datasets by identifying each statistical unit according to its enterprise code (the enterprise is the legal unit), and retaining it in the final data set of firms that responded to all three CIS. We restrict our analysis to the sample that resulted from the merger.

Because some information on turnover and size is missing in the CIS for 1992, another set of data is used to provide more information about the firms obtained from merging the three waves of the CIS. We use the annual enterprise surveys to complete this missing 1992 information, notably for turnover, size and industrial activity.

We obtained a total of 1,074 manufacturing firms, with 20 or more employees, for the three time periods: t1, 1994 to 1996; t2, 1998 to 2000 and t3, 2002 to 2004 (see Table 1 for the structure of the dataset).

INSERT TABLE 1 ABOUT HERE

It should be noted that the raw data from the three waves of the CIS that we use, have a very different construction. These surveys are not conducted at regular intervals and do not cover the same sample of firms; the samples are constructed using stratified sampling methods in

⁸ The ‘enquête annuelle entreprises’ are French surveys conducted by Sessi, the Ministry of Agriculture (for IAA) and INSEE (the French public Institute of Statistics). These longitudinal datasets provide yearly information on French firms’ balance sheets for firms that have 20 employees or more.

¹⁰ The European Union’s industrial classification of economic activities, recognized by the Accounting Economic System (National Institute of Statistics).

which firm size and industry are key parameters; and the sampling methodology differs from one wave to another. This implies that the firms surveyed in successive waves may not be the same.

As a result, it is difficult to detect which firm entries and exits are due to economic causes and which are caused by random sampling. We are not able to evaluate the general characteristics of firms that exit and enter in our sample (i.e. we cannot analyse attrition). For example, in CIS2 and CIS3, census data are used to identify firms with at least 500 employees and a stratified random sample (by size and economic activity) is applied for firms with less than 500 employees. The same rules are used for CIS4, but a cut-off point of 250 employees is applied. In addition, some CIS waves use a minimum of 10 employees as the criterion for inclusion, while others include apply the criterion of 20 employees. CIS2 systematically includes firms with more than 20 employees, while CIS4 includes firms with at least 10 employees. In CIS3, stratification by size differs: for manufacturing sectors the firms surveyed have a minimum of 20 employees, but in the services sector firms with a minimum of 10 employees are included. Moreover, while the first and the last waves of the CIS apply exclusively to firms in the manufacturing industry, CIS3 and CIS4 include services (services in the widest sense are included in CIS4; CIS3 includes only selected services fields).

Given these limitations, we think that our sample of 1,074 firms is a good approximation of CIS firms. Table 2 provides information on the distribution of the data by sector. Given that we use CIS data which provide information only on industrial firms, our final dataset includes industrial activities. This is in line with previous work on firm growth and innovation (Mansfield, 1962; Evans, 1987a, 1987b). Electrical engineering, wood, paper and printing, chemical, metal and machinery activities account for more than 10% each, with the remaining economic activities represented in our sample accounting for less than 10% of the observations. A similar distribution characterises the CIS, with the exception of textile that is less represented in our sample.

INSERT TABLE 2 ABOUT HERE

Table 3 shows the sample and CIS distribution by size in the period under scrutiny. Our sample comprises mainly large firms with more than 250 employees (approximately 75.76 %). Medium-sized firms represent about 19 % of the sample, with small firms with less than 50 employees accounting for 5.34 %. The distribution by size of CIS firms is similar: large

firms with more than 250 employees account for 80.34 %, medium-sized firms represent about 10.96 %, and small firms with less than 50 employees represent about 8% of the total.

INSERT TABLE 3 ABOUT HERE

Table 4 compares the proportion of innovative firms in CIS and in our sample. It shows that firms in our sample are in general less innovative than the firms surveyed in CIS. In particular, 43.2 % of the companies of our sample are product or process innovators; for the total manufacturing firms surveyed in CIS, this percentage is 52.3 %.

INSERT TABLE 4 ABOUT HERE

2.2. Definition of the variables

2.2.1. Growth rates

For each year, starting from 1994, we compute firm growth rates following two different methods.

We first define a firm's rate of growth as the log-difference of size:

$$Growth_{i,t} = \ln(S_{i,t}) - \ln(S_{i,t-1}),$$

where $S_{i,t}$ is firm turnover at time t , deflated using the French GDP deflator (base year 2000) drawn by Thomson Datastream, and $S_{i,t-1}$ is its lagged value¹¹.

Second, we compute the compound average growth rate (CAGR), which provides a theoretical growth rate, assuming steady growth over the period t_0 - t_n , and hence takes into account that each time period covers more than one year.¹²

$$CAGR_{i,t} = \left(\frac{Turn_{i,t_n}}{Turn_{i,t_0}} \right)^{\frac{1}{n-t_0}} - 1$$

¹¹ Firm growth can be measured using various indicators, such as sales, employment or assets. However, as Table 0 suggests, the stream of literature related to this paper analysing the effects of innovation on firms' growth adopts sales as a proxy for size. Also, while the links between innovation and employment, and between innovation and assets, undoubtedly are important, they refer to rather different theoretical backgrounds aimed at capturing different dynamics, which are not the focus of this paper.

¹² The log-difference is the most widespread measure of sales growth used in the literature. However, in our case, it may have some drawbacks due to the fact that the firm observations do not correspond to consecutive years. For this reason we also use the CAGR index, which also provides a measure that assumes a steady growth rate, but we think that both are worth including.

Figure 1 shows the distribution of firm growth rates. It shows that the empirical distribution of growth rates in our sample is more Laplacian than Gaussian. This is in line with work that analyses the distribution of firm growth rates (Bottazzi *et al.*, 2007; Bottazzi and Secchi, 2003; Castaldi and Dosi, 2009). In particular, the mean growth rate for the whole period is approximately 20% for both measures used, but their standard deviations show wide variations because of the large time span (1992-2004). Consequently, it is useful to analyse the distribution of growth rates as a function of innovation distribution. We expect innovation to have a positive impact on firm growth.

2.2.2. Innovation

The goal of our analysis is not an extensive overview of the corporate growth of the firms in the CIS samples, but observation of the interactions between innovation and growth. Consequently, the definition of our innovation variables is crucial.

We employ two main variables: the first measures product innovation; the second measures process innovation. In the CIS, a firm is considered to be ‘innovative’ if, over a given period of time (the previous three years), it introduced a new product or a new process. This information is gathered through a set of:

(1) dichotomous variables that reveal whether or not the firm produced an innovation during the period covered by the survey;

(2) quantitative variables based on firms’ responses to a question about the percentage of sales due to the commercialization of new products (new goods and services).¹³ Since these variables can be used to proxy for the commercial success of innovations, they are being used increasingly in the empirical literature (Mairesse and Mohnen, 2010).

While product innovations are associated with more radical technologies and are expected to result in higher growth rates because of their higher economic returns, process innovations are based on more defensive technological strategies. However, the effects of product and process innovations are linked indirectly and lead to new types of products (Barras, 1990). We constructed a set of dichotomous variables:

Ino, taking the value 1 if the firm has introduced *either* a product *or* a process innovation;

¹³ CIS questionnaire.

Inop, taking the value 1 if the firm has introduced a product innovation;

Inoc, taking the value 1 if the firm has introduced a process innovation.

A second set of information on innovation provided by CIS is quantitative and estimates the share of innovative products and marginally modified products in turnover (respectively Inoprod and Inoproc). However, while firms generally are able to quite easily quantify the share of turnover from product innovation, they are often less able to give the same information for process innovation. For this reason we use only Inoprod and drop Inoproc. Descriptive statistics are presented in Table 5.

INSERT TABLE 5 ABOUT HERE

3. Methodology

We start our empirical analysis by comparing the growth rate distribution among different firm types - innovative vs non-innovative firms. To this end, we perform a two-sample Fligner-Policello robust rank order test. This test is a useful alternative to the Mann-Whitney-Wilcoxon test as in the Fligner-Policello test the assumption of the underlying sample distributions being the same is dropped.¹⁴ This test confirms the null hypothesis that the two groups of firms, innovating and non-innovating, are sampled from the same population. We define innovating firms as those firms that introduced either a product or a process innovation during the period under scrutiny. As we are also interested in differentiating between the roles of product and process innovation, we also distinguish between product and process innovating firms. The results of the Fligner-Policello test are presented in Table 6. The test rejects the null hypothesis of an equal distribution between innovators and non-innovators. The same null hypothesis is also rejected for product innovators and non-innovators, and process innovators and non-innovators. These results suggest that innovating firms generally perform better than non-innovators.

INSERT TABLE 6 ABOUT HERE

After testing for whether innovation can be considered a source of growth differentials, we analyse the effects of innovative activities on firm growth. Studying the determinants of firm growth poses some methodological issues, in particular, with respect to how they relate to the

¹⁴ The two-sample Fligner-Policello robust rank order test assumes neither normality nor equal variance, nor equal shape.

distributional properties of growth rates, and their persistence over time. Below, we discuss how we address these methodological issues.

In the empirical analysis, we use a Gibrat-like model that includes firm size as an explanatory variable. The empirical literature uses two different specifications for testing Gibrat's Law. Since our objective is not to test the validity of the law, but to verify the impact of innovation on firm growth, we use both specifications in order to check the consistency and robustness of our results to the use of different specifications and estimations techniques.

The first specification to model growth in firms' turnover as a function of firm innovation follows the original logarithmic representation in Gibrat's Law:

$$\ln(S_{i,t}) = \lambda_1 + \lambda_2 \ln(S_{i,t-1}) + \lambda_3 Ino_{i,t-1} + \sum \omega_j + \sum \psi_t + \varepsilon_{i,t} \quad (1)$$

where $S_{i,t}$ and $S_{i,t-1}$ represent turnover (deflated) for firm i at time t and $t-1$, respectively, $Ino_{i,t-1}$ is product or process innovation for firm i at time $t-1$. ω_j and ψ_t represent a set of industry¹⁵ and time dummies, controlling respectively, for macroeconomic and time fluctuations. The inclusion of the lagged dependent variable in the model requires dynamic estimation techniques. We have a large N and small T panel data set. Following the literature on dynamic panel estimators (Arellano and Bond 1991; Blundell and Bond 1998; Bond 2002), equation (1) is estimated using the Generalised Method of Moments (GMM) methodology. In particular, to increase efficiency, we use the GMM-System (GMM-SYS) estimator developed by Blundell and Bond (1998). Blundell and Bond demonstrate dramatic improvement in the performance of the system estimator compared to the usual first-difference GMM estimator developed by Arellano and Bond (1991). By using instrumental variables in levels with lagged first-differenced terms, this approach, allows us to control for endogeneity of the innovation variables.

Transforming Equation (1), we obtain an alternative specification of Gibrat's Law as follows:

$$Growth_{i,t} = \lambda_1 + \lambda_2 \ln(S_{i,t-1}) + \lambda_3 Ino_{i,t-1} + \omega_i + \sum \psi_t + \varepsilon_{i,t} \quad (2)$$

Equation (2) can be estimated using traditional panel data techniques implementing the fixed effects estimator. As a robustness check, we also estimate the model using Ordinary Least Squares (OLS). Finally, to provide further evidence on the relationship between firm growth and innovation, we estimate Equation (2) by means of quantile regressions. This approach is

¹⁵ The industrial context is important because innovation is 'industry context specific' (Dosi, 1988). Thus, we need to control for industry effects.

relevant for our analysis since growth rate distributions appear to be fat-tailed (see Figure 1). In the OLS and quantile regressions we also include a set of industry dummies in order to control for sectoral specificities.

A second methodological issue that needs to be taken into account in our analysis is related to serial correlation in firms' annual growth rates. While debate on this issue remains ongoing, previous works have found evidence of persistence in growth rates (Chesher, 1979; Geroski *et al.*, 1997; Bottazzi and Secchi, 2006; Coad, 2007; Coad and Hözl, 2011). To control for any growth autocorrelation, we test an additional specification that includes the lagged growth rates as an explanatory variable. Thus, an alternative specification of our model can be written as:

$$Growth_{i,t} = \lambda_1 + \lambda_2 Growth_{i,t-1} + \lambda_3 \ln(S_{i,t-1}) + \lambda_4 Ino_{i,t-1} + \sum \omega_j + \sum \psi_t + \varepsilon_{i,t} \quad (3)$$

Since Equation (3) includes the lagged dependent variable among the explanatory variables, it is estimated using the GMM-SYS methodology discussed above.

4. Results

The results of the econometric estimations are presented in Tables 7-12, which show the results for different equations, estimation techniques and variables.

4.1. General results

We start by commenting on the results of the estimations related to equation (1), which represents Gibrat's Law in its classical form (Table 7). Our basic results confirm that innovation has a positive and significant impact on the rate of firm growth. The variable *Ino*, which takes the value 1 if the firm has introduced either a product or a process innovation, is positively and significantly ($p < 0.05$) related to the rate of firm growth. We also wanted to figure out the nature of the impact of innovation on firm growth. If we consider product (*Inop*) and process innovation (*Inoc*) separately, we find that both types of innovation have a positive and significant impact on firm growth ($p < 0.05$ and $p < 0.01$, respectively). We also test the sensitivity of the impact of product innovation on firm growth to the definition of the innovation variable. If innovation is expressed as a quantitative variable (*Inoprod*), we observe that the coefficient remains positive and significant ($p < 0.10$).

Our results also confirm that small companies grow more than large ones, as shown by the coefficient of $\text{Ln}(S_{t-1})$, which is found to be less than 1 and significant at the 1% level.

In order to shed further light on the relationship between innovation and growth, Equation (2) analyses an alternative specification of Gibrat's Law (8-11). This can be estimated by means of quantile regressions, which allow us to analyse the heterogeneity in the returns to innovation. Table 8 shows the results obtained by using *Ino* as a proxy for innovation activities. Let us recall that this variable is related to both product and process innovation. The evidence obtained by applying the quantile regression suggests that, although innovation exert a positive effect on firms' growth, this effect is stronger for firms in the uppermost quantile than for firms in the lower quantiles. This means that, for high-growth firms, innovative activity makes an important contribution to their superior growth performance (in line with the findings in Coad and Rao, 2008).

In Tables 9 -11 we disentangle the differential impact of product and process innovation from the general effect. Actually, as it is showed in Table 9, product innovation appears to have a stronger impact for firms in the uppermost quantile. This evidence is also confirmed when we use as an explanatory variable an alternative definition of product innovation (Table 10), although the results are less marked when we use the quantitative variable (*Inoprod*). The difference with the previous estimation clearly is due to the differences in the nature of the variables (quantitative versus categorical). Indeed, *Inoprod* represents an estimation of the percentage of sales due to the commercialisation of new products. As Mairesse and Mohnen (2010) note,¹⁶ this variable is less reliable than qualitative variables since firms may encounter difficulties in quantifying the share of their turnover due to the commercialisation of product innovations. Nevertheless, the significant coefficients in Table 10 suggest that the results are in line with the previous estimations.

When one focuses on the specific effect of process innovation (Table 11), the results of the quantile regression suggest instead that the impact is stronger for firms at the 25th percentile than for the other ones. All in all, these results provide further support to the well known framework linking innovation to firms' lifecycles (Abernathy and Utterback, 1978).

¹⁶ These two authors analyse the quality of CIS data noting that: 'Many of the variables, qualitative and quantitative as well, are of a subjective nature, being largely based on the personal appreciation and judgment of the respondents. One of the most interesting variables and that is relatively well known, the share in total sales due to new products, has, for example, values that tend to be rounded (10%, 15%, 20%, ...), attesting to its subjective nature and suggesting that perhaps we should treat it as a categorical variable and not make too much out of its continuous variations' (Mairesse and Mohnen, 2010: 9).

According to this frame of analysis, firms in the fast growing stages of their lifecycle are mostly focused on the introduction of product innovations which make it possible to gain further market shares and sustain the growth process. On the contrary, firms in the maturity stage characterized by decreasing growth rates are more interested in the introduction of process innovations which allows for preserving competitiveness by lowering production costs.

4.2. Robustness checks

To check for the robustness of our results we propose a number of different estimations. First of all, all the estimations presented in Tables 7 through 12 have been run by using an alternative measure of firm growth rates (CAGR).

All the results are robust to the different measures of firm growth rates, but the coefficients when Growth is the dependent variable are higher than when CAGR is the dependent variable. This can be interpreted using the descriptive statistics reported in Table 6. Since CAGR is calculated on the basis of the assumption of steady growth, it provides a relatively smooth picture of the growth process versus that obtained using the log-difference indicator. The average value of CAGR is lower than the value of Growth, and for this reason, the effects of innovation on CAGR also appear quite smooth.

It is also important to check the robustness of our analysis by estimating Equation (2) using alternative estimation techniques other than quantile regression. In particular we show the results obtained by implementing OLS, fixed and random effects (Tables 8-11). We find again that small companies grow more than large ones, shown by the negative and significant coefficient of $\text{Ln}(S_{i,t-1})$. More important, our results confirm that innovation has a positive and significant impact on firms' growth rates in all the estimations, a result that is robust to the use of alternative estimators. For product innovation (Tables 9 and 10) and process innovation (Table 11), we find similar and even more robust results. When we test the sensitivity of the impact of product innovation on a firm's growth, to the definition of the innovation variable, we find that the results are less robust if we use the quantitative variable (*Inoprod*).

Finally, we test an additional specification (see Equation 3) in order to control for autocorrelation among growth rates (Table 12). While we do not find any serial correlation in

annual growth rates for the firms in our sample, our basic results related to the relationship between innovation and growth are confirmed when we use this alternative specification.¹⁷

INSERT TABLE 7 to 12 ABOUT HERE

5. Conclusion

Our empirical study based on French CIS data for the period 1992-2004 enables us to complement the literature on firm growth and to respond to the issues noted in the introduction. Our main findings can be summarised as follows.

First, innovative firms (whatever the type of innovation) produce more growth than non-innovative firms.

Second, the estimation techniques mostly yield quite robust results for the qualitative innovation variables. The exception is the Inoprod variable which is the quantitative innovation variable. The use of a quantitative variable for product innovators sometimes results in non-significant outcomes due to the peculiarity of this variable.

Third, we use two indicators for firm growth. Our study shows that the results obtained are definitively robust to the dependent variable measurement method. In general, the coefficients are higher with Growth than with CAGR.

Fourth, the results of the quantile regressions are in line with other studies (Coad and Rao, 2008): the effects of innovation on growth are stronger on firms with the highest growth rates.

The results of our analysis have clear implications for innovation policy. First, since our analysis consider the output of innovation activities rather than the typical input measure such as R&D investments, we would propose that innovation policies should care not only about the support to R&D investments (like tax credits policies), but they should also care about the output of the innovation process, and in particular about the differential impacts of product and process innovation.

Moreover, the effects of innovation appears to be different also across different quantiles. In particular, when considering innovation outputs as a whole, this variable shows the higher

¹⁷ Overall, the coefficients of product/process innovation are consistent with the previous estimations. The differences between CAGR and Growth remain due to the different specifications of the two variables.

coefficient for firms in the uppermost quantile. However, when distinguishing between process and product innovation, our results suggest that product innovation exert a stronger impact for firms in the uppermost quantile, while process innovation shows a higher coefficients for firms in the lowermost quantile. This would suggest that targeted innovation policies should care about the firms' idiosyncratic features, and in particular about their relative position in the firm lifecycle.

Our analysis also leaves some interesting questions unanswered, which would open some avenues for future research. For example, it might be interesting were policy makers to experiment with policy tools in order to analyse their effectiveness. With this objective in mind, we would add other variables to our panel model (e.g. whether firms receive tax credits, and among those that do whether they experience higher growth). Within the framework proposed, it is possible to provide a more accurate assessment of public technology support.

While the present study provides new insight on the impact of innovation on firm performance in terms of growth, it would be interesting in future research to analyse the persistence of innovation. For example, in the present study we do not examine whether some firms innovate persistently while others do not. Our longitudinal data would allow us to determine whether firms that persistently innovate grow more than sporadic innovators.

Appendix.

Table 0. Empirical studies on the relation between firm growth and innovation

<i>Study</i>	Country and time period	Measure for firm size and growth rate (Type of data)	Measure for innovation activity	Main results
<i>Mansfield (1962)</i>	USA, 10 enterprises and 10 aggregated industries (1916-1954)	Minimum efficient size, relative size variation (Individual data)	Successful innovations determine if a firm is an innovator or not	The firms that carried out significant innovations grew more rapidly than the others
<i>Geroski et al.(1993)</i>	U-K large quoted firms (1976-1982)	Profit margins and indirect measure of size: market concentration (Panel of 721 firms)	Number of innovations produced by each innovating firm	The number of innovations (number of patents) has no impact on corporate growth
<i>Ernst (2001)</i>	German machine tool manufacturers (1984-1992)	Sales (panel of 50 firms)	Patent applications (German and European patent system)	Patents increase sales with a 2 or 3 years lag
<i>Del Monte and Papagni (2003)</i>	Italian manufacturing firms (1989-1997)	Return on sales (panel of 500 firms)	Research Intensity	Correlation between Growth rate and Research Intensity
<i>Cefis and Marsili (2005)</i>	Netherland manufacturing firms (1996-2003)	Survival time (panel of 3 275 manufacturing firms)	The introduction of an innovation on the market and innovation type	The innovating firms extend their life in the industry
<i>Coad and Rao (2008)</i>	Large sample (world) of high-tech firms (1963-1998)	Total sales (panel of 4012 firms in high-tech sectors)	Innovativeness index (measure of patent activity and R&D expenditures)	Innovation more crucial for the growth of 'rapid-growth firms'
<i>Cassia et al. (2009)</i>	U-K public companies (1995-2006)	Total sales (Panel of 200 firms)	Universities, Knowledge, Inputs and Outputs	Effects on firm growth
<i>Corsino and Gabriele (2010)</i>	Worldwide firms from semiconductors (1998-2004)	Total sales (panel of 95 firms)	Innovations counts	Product innovations affect firm growth

Table 1. The structure of the final panel

year	Time	Growth_t	Growth_{t-1}	Inno_t	Inno_{t-1}
1992-1994	T0	G ₀	.	.	.
1994-1996	T1	G ₁	G ₀	Inno ₁	.
1998-2000	T2	G ₂	G ₁	Inno ₂	Inno ₁
2002-2004	T3	G ₃	G ₂	Inno ₃	Inno ₂

Table 2. Sample distribution by industry

	Nace Rev 1.1	Sample	CIS
		%	%
Mining and quarrying	10-14	0.84	1.48
Textiles	17-19	8.47	14.23
Wood/paper/printing	20-22	12.20	10.62
Chemicals	23-24	12.48	10.17
Plastic /Rubber	25	6.15	7.35
Glass/ceramics	26	5.68	4.30
Metals	27-28	12.66	16.14
Machinery	29	10.43	11.05
Electrical engineering	30-33	14.15	12.15
Vehicles	34-35	8.94	5.23
Furniture/recycling	36-37	4.84	5.80
Energy	40-41	3.17	1.48
Total		100	100

Table 3. Sample distribution by size

Size class	Sample	CIS
	%	%
20 - 49	5.34	8.69
50- 249	18.90	10.96
>250	75.76	80.34
Obs	100	100

Table 4. Proportion of innovative firms in CISs and in the sample used in the empirical analysis (%)

	Sample	CIS
	%	%
Product innovators	39.7	33.6
Process innovators	40.9	43.1
Product or process Innovators	43.2	52.3

Figure 1. Growth rates distribution

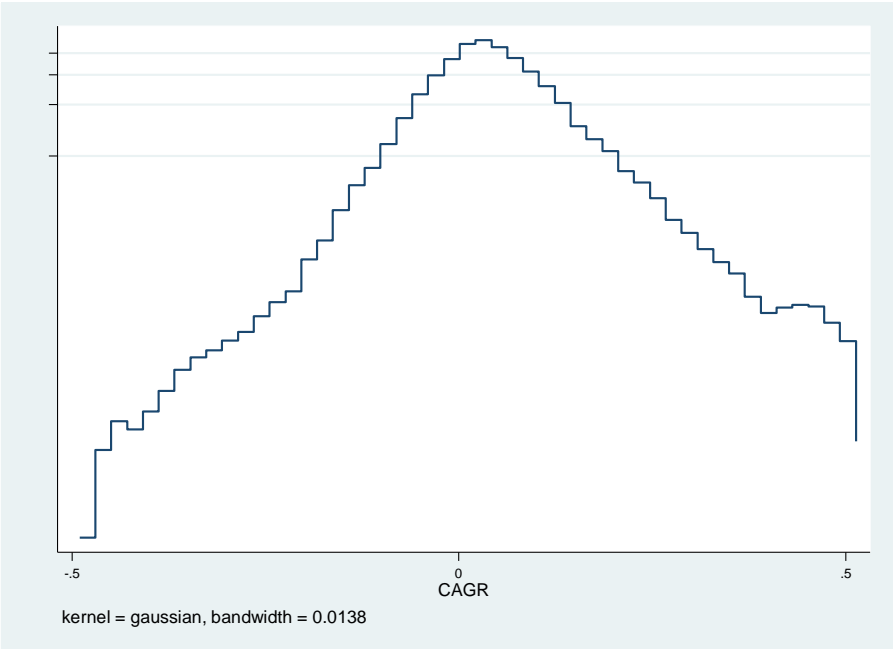
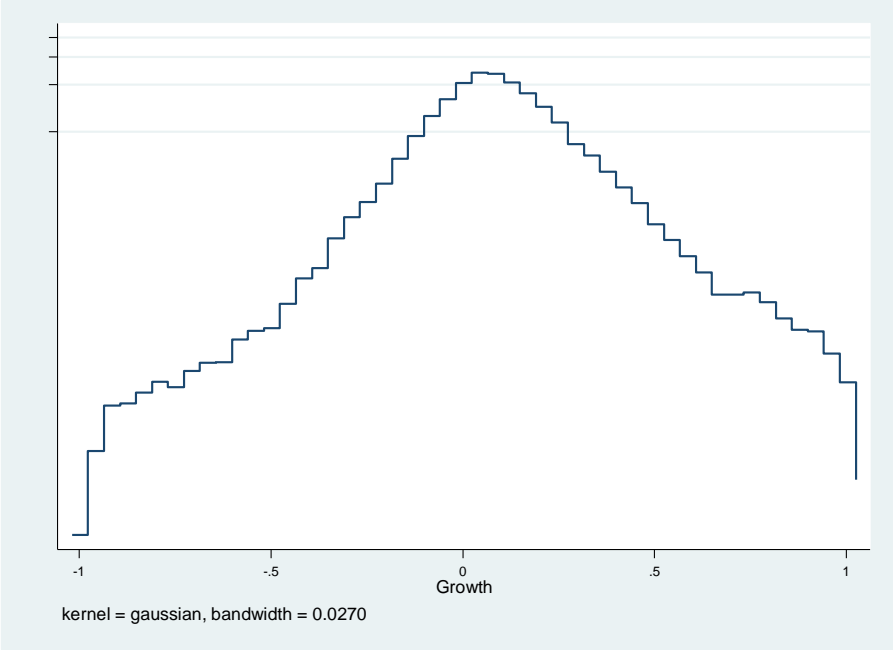


Table 5. Summary statistics

<i>Variable</i>	<i>Obs.</i>	<i>Mean</i>	<i>Std. Dev.</i>	<i>Min</i>	<i>Max</i>
<i>ln(S_{i,t})</i>	3222	7.417175	1.756326	1.410513	14.49669
<i>ln(S_{i,t-1})</i>	2822	7.591357	1.600403	2.633156	14.48141
<i>Growth</i>	2822	0.0854136	0.2754607	-1.516976	2.377159
<i>Lag_growth</i>	2750	0.1577891	1.512188	-3.521861	10.91398
<i>CAGR</i>	2822	0.0545427	0.1733176	-0.531626	2.282415
<i>Ino</i>	2390	0.6355649	0.4813721	0	1
<i>Inop_{i,t-1}</i>	2380	0.4331933	0.4956209	0	1
<i>Inoc_{i,t-1}</i>	2397	0.5127242	0.4999424	0	1
<i>Inoprod_{i,t-1}</i>	1025	-2.490742	1.123468	-4.61512	0

Table 6. Two-Sample Fligner-Policello Robust Rank Order Test

<i>Growth</i>	<i>Obs.</i>	<i>Average placement</i>	<i>Index of variability</i>	<i>u</i>	<i>2-tailed p-value</i>
<i>Non-innovators</i>	610	2.1e+02	1.1e+07	-3.117	0.0018
<i>Innovators</i>	463	3.4e+02	1.3e+07		
<i>Non-innovators</i>	610	1.8e+02	8.7e+06	-2.770	0.0056
<i>Product Innovators</i>	402	3.4e+02	1.1e+07		
<i>Non-innovators</i>	610	1.9e+02	9.8e+06	-2.981	0.0029
<i>Process Innovators</i>	423	3.4e+02	1.2e+07		
<i>CAGR</i>	<i>Obs.</i>	<i>Average placement</i>	<i>Index of variability</i>	<i>u</i>	<i>2-tailed p-value</i>
<i>Non-innovators</i>	610	2.0e+02	1.1e+07	-3.290	0.0010
<i>Innovators</i>	463	3.4e+02	1.3e+07		
<i>Non-innovators</i>	610	1.8e+02	8.8e+06	-2.953	0.0031
<i>Product Innovators</i>	402	3.4e+02	1.1e+07		
<i>Non-innovators</i>	610	1.9e+02	9.9e+06	-3.160	0.0016
<i>Process Innovators</i>	423	3.4e+02	1.2e+07		

Table 7. Estimates of the growth of firms' turnover (equa. 1).

VARIABLES	(1) GMM-SYS	(2) GMM-SYS	(3) GMM-SYS	(4) GMM-SYS	(5) GMM-SYS
<i>Ln(S_{i,t-1})</i>	0.986*** (0.0155)	0.976*** (0.0150)	0.977*** (0.0148)	0.975*** (0.0146)	0.927*** (0.0328)
<i>Ino_{i,t-1}</i>		0.0352** (0.0154)			
<i>Inop_{i,t-1}</i>			0.0307** (0.0136)		
<i>Inoc_{i,t-1}</i>				0.0394*** (0.0136)	
<i>Inoprod_{i,t-1}</i>					0.0138* (0.00793)
<i>Constant</i>	0.0694 (0.0942)	0.113 (0.104)	0.250** (0.114)	0.117 (0.0878)	0.565** (0.235)
<i>D_Industry</i>	yes	yes	yes	yes	yes
<i>D_Year</i>	yes	yes	yes	yes	yes
<i>Observations</i>	2822	2367	2357	2374	1015
<i>Number of ID</i>	1073	1070	1070	1072	600

Notes:*** p<0.01, ** p<0.05, * p<0.1. Standard errors in parentheses.

Table 8. Estimates of the growth rate (equa. 2).

VARIABLES	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)
	OLS		FE		RE		Quantile					
	Growth	CAGR	Growth	CAGR	Growth	CAGR	Growth			CAGR		
							q25	q50	q75	q25	q50	q75
$Ln(S_{i,t-1})$	-0.0211*** (0.00371)	-0.0123*** (0.00222)	-0.430*** (0.0203)	-0.264*** (0.0117)	-0.0284*** (0.00435)	-0.0189*** (0.00275)	-0.00674*** (0.00241)	-0.00879*** (0.00226)	-0.0163*** (0.00380)	-0.00311** (0.00154)	-0.00453*** (0.00119)	-0.00870*** (0.00225)
$Ino_{i,t-1}$	0.0451*** (0.0114)	0.0253*** (0.00684)	0.0317** (0.0148)	0.0148* (0.00848)	0.0481*** (0.0118)	0.0270*** (0.00708)	0.0312*** (0.00613)	0.0252*** (0.00783)	0.0389*** (0.00682)	0.0150*** (0.00450)	0.0130*** (0.00450)	0.0208*** (0.00670)
<i>Constant</i>	0.0927** (0.0377)	0.0545** (0.0226)	3.680*** (0.169)	2.264*** (0.0968)	0.137*** (0.0454)	0.0960*** (0.0289)	-0.0234 (0.0261)	0.0450** (0.0203)	0.131*** (0.0278)	-0.0126 (0.0128)	0.0231** (0.0104)	0.0683*** (0.0183)
$D_{Industry}$	yes	yes	no	no	yes	yes	yes	yes	yes	yes	yes	Yes
D_{Year}	yes	yes	yes	yes	yes	yes	yes	yes	yes	yes	yes	Yes
<i>Observations</i>	2367	2367	2367	2367	2367	2367	2367	2367	2367	2367	2367	2367
<i>R-squared/pseudo</i>	0.073	0.065	0.329	0.347	0.1274	0.124	0.0296	0.0422	0.0664	0.0322	0.0457	0.0711
<i>Number of ID</i>			1070	1070	1070	1070						

$Ino_{i,t-1}$ is a dummy variable taking the value 1 if the company has introduced either a new product or a new process on the market.

Notes: *** p<0.01, ** p<0.05, * p<0.1. Standard errors in parentheses.

Table 9. Estimates of firm growth rate (measured by growth and GAGR)

VARIABLES	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)
	OLS		FE		RE		Quantile					
	Growth	CAGR	Growth	CAGR	Growth	CAGR	Growth			CAGR		
							q25	q50	q75	q25	q50	q75
$Ln(S_{i,t-1})$	-0.0204*** (0.00366)	-0.0117*** (0.00220)	-0.430*** (0.0204)	-0.264*** (0.0117)	-0.0273*** (0.00431)	-0.0179*** (0.00273)	-0.00468 (0.00329)	-0.00991*** (0.00281)	-0.0144*** (0.00376)	-0.00228 (0.00190)	-0.00498*** (0.00146)	-0.00782*** (0.00158)
$Inop_{i,t-1}$	0.0413*** (0.0109)	0.0212*** (0.00654)	0.0329** (0.0139)	0.0124 (0.00797)	0.0424*** (0.0113)	0.0211*** (0.00678)	0.0312*** (0.00945)	0.0325*** (0.00882)	0.0367*** (0.0110)	0.0153*** (0.00580)	0.0163*** (0.00344)	0.0202*** (0.00493)
<i>Constant</i>	0.0957** (0.0378)	0.0553** (0.0227)	2.803*** (0.134)	1.734*** (0.0770)	0.281*** (0.0770)	0.181*** (0.0490)	-0.0611 (0.0731)	0.128*** (0.0302)	0.258*** (0.0686)	-0.0298 (0.0420)	0.0646*** (0.0190)	0.137*** (0.0270)
$D_Industry$	yes	yes	no	no	yes	yes	yes	yes	yes	yes	yes	yes
D_Year	yes	yes	yes	yes	yes	yes	yes	yes	yes	yes	yes	yes
<i>Observations</i>	2357	2357	2357	2357	2357	2357	2357	2357	2357	2357	2357	2357
<i>R-squared/pseudo</i>	0.072	0.064	0.329	0.346	0.126	0.121	0.0290	0.0445	0.0668	0.0315	0.0479	0.0717
<i>Number of ID</i>			1070	1070	1070	1070						

$Inop_{i,t-1}$ is a dummy variable taking the value 1 if the company has introduced a new product on the market.

Where *Growth* is measured using the first difference equation

Notes:*** p<0.01, ** p<0.05, * p<0.1. Standard errors in parentheses.

Table 10. Estimates of firm growth rate (measured by growth and GAGR)

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)
	OLS		FE		RE		Quantile					
	Growth	CAGR	Growth	CAGR	Growth	CAGR	Growth			CAGR		
VARIABLES							q25	q50	q75	q25	q50	q75
$Ln(S_{i,t-1})$	-0.0224*** (0.00579)	-0.0133*** (0.00345)	-0.365*** (0.0344)	-0.218*** (0.0187)	-0.0271*** (0.00629)	-0.0197*** (0.00407)	-0.00731 (0.00844)	-0.0132*** (0.00402)	-0.0197*** (0.00644)	-0.00373 (0.00440)	-0.00663** (0.00258)	-0.0106*** (0.00236)
$Inoprod_{i,t-1}$	0.0136** (0.00672)	0.00984** (0.00401)	0.0130 (0.0104)	0.00667 (0.00567)	0.0129* (0.00682)	0.00843** (0.00408)	-0.00263 (0.00670)	0.00784** (0.00317)	0.0141** (0.00585)	-0.00131 (0.00380)	0.00391*** (0.00147)	0.00757** (0.00383)
<i>Constant</i>	0.332*** (0.0944)	0.205*** (0.0563)	3.400*** (0.304)	2.022*** (0.165)	0.244* (0.136)	0.176** (0.0867)	0.0459 (0.195)	0.112 (0.146)	0.293*** (0.0887)	0.0236 (0.0841)	0.0537 (0.0745)	0.154** (0.0697)
$D_Industry$	yes	yes	no	no	yes	yes	yes	yes	yes	yes	yes	yes
D_Year	yes	yes	yes	yes	yes	yes	yes	yes	yes	yes	yes	yes
<i>Observations</i>	1015	1015	1015	1015	1015	1015	1015	1015	1015	1015	1015	1015
<i>R-squared/pseudo</i>	0.096	0.093	0.298	0.327	0.133	0.145	0.0344	0.0616	0.1008	0.0302	0.0572	0.0946
<i>Number of ID</i>			600	600	600	600						

$Inoprod_{i,t-1}$ is the share of product innovation on turnover, where *Growth* is measured using the first difference equation.

Notes:*** p<0.01, ** p<0.05, * p<0.1. Standard errors in parentheses.

Table 11. Estimates of firms growth rate (measured by growth and GAGR)

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)
	OLS		FE		RE		Quantile					
VARIABLES	Growth	CAGR	Growth	CAGR	Growth	CAGR		Growth		CAGR		
							q25	q50	q75	q25	q50	q75
<i>Ln(S_{t-1})</i>	-0.0203*** (0.00365)	-0.0119*** (0.00218)	-0.430*** (0.0203)	-0.265*** (0.0116)	-0.0276*** (0.00428)	-0.0185*** (0.00271)	-0.00659* (0.00375)	-0.00825*** (0.00195)	-0.0148*** (0.00297)	-0.00313** (0.00144)	-0.00442*** (0.00106)	-0.00775*** (0.00255)
<i>Inoc_{i,t-1}</i>	0.0421*** (0.0108)	0.0233*** (0.00648)	0.0301** (0.0132)	0.0158** (0.00758)	0.0453*** (0.0110)	0.0257*** (0.00660)	0.0310*** (0.00742)	0.0220*** (0.00797)	0.0252** (0.0114)	0.0151*** (0.00304)	0.0115*** (0.00399)	0.0127*** (0.00490)
<i>Constant</i>	0.203*** (0.0637)	0.120*** (0.0382)	3.684*** (0.169)	2.266*** (0.0967)	0.140* (0.0738)	0.0973** (0.0471)	-0.0921 (0.0935)	0.0615 (0.0631)	0.164 (0.109)	-0.0455 (0.0493)	0.0325** (0.0140)	0.0849* (0.0439)
<i>D_Industry</i>	yes	yes	no	no	yes	yes	yes	yes	yes	yes	yes	yes
<i>D_Year</i>	yes	yes	yes	yes	yes	yes	yes	yes	yes	yes	yes	yes
<i>Observations</i>	2374	2374	2374	2374	2374	2374	2374	2374	2374	2374	2374	2374
<i>R-squared/pseudo</i>	0.072	0.065	0.328	0.347	0.126	0.124	0.0297	0.0414	0.0645	0.0326	0.0451	0.0694
<i>Number of ID</i>			1072	1072	1072	1072						

Where *Inoc* is a dummy variable taking the value 1 if the company has introduced a new process on the market.

Notes:*** p<0.01, ** p<0.05, * p<0.1. Standard errors in parentheses.

Table 12. Estimates of the firms' growth rate measured by growth and GAGR (equa. 3)

VARIABLES	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
	GMM-SYS		GMM-SYS		GMM-SYS		GMM-SYS		GMM-SYS	
	Growth	CAGR	Growth	CAGR	Growth	CAGR	Growth	CAGR	Growth	CAGR
$growth_{t-1}$	0.0315 (0.0355)	0.00288*** (0.000216)	0.0566 (0.0358)	0.00315*** (0.000170)	0.0565 (0.0360)	0.00311*** (0.000162)	0.0587 (0.0357)	0.00314*** (0.000163)	0.159* (0.0942)	0.0425 (0.0613)
$Ln(S_{i,t-1})$	-0.0332*** (0.00458)	-0.0196*** (0.00326)	-0.0326*** (0.00495)	-0.0183*** (0.00319)	-0.0319*** (0.00466)	-0.0177*** (0.00292)	-0.0321*** (0.00482)	-0.0180*** (0.00309)	-0.0329*** (0.00794)	-0.0207*** (0.00473)
$Ino_{i,t-1}$			0.0438*** (0.0122)	0.0240*** (0.00720)						
$Inop_{i,t-1}$					0.0399*** (0.0115)	0.0196*** (0.00668)				
$Inoc_{i,t-1}$							0.0444*** (0.0113)	0.0241*** (0.00653)		
$Inoprod_{i,t-1}$									0.0149** (0.00754)	0.00827** (0.00421)
Constant	0.256*** (0.0716)	0.121*** (0.0227)	0.278*** (0.0724)	0.101*** (0.0211)	0.267*** (0.0747)	0.0987*** (0.0240)	0.267*** (0.0729)	0.162*** (0.0294)	-0.0141 (0.198)	0.142** (0.0612)
Observations	2750	2750	2334	2334	2324	2324	2341	2341	1001	1001
Number of ID	1073	1073	1070	1070	1069	1069.	1072	1072	598	598

Notes:*** p<0.01, ** p<0.05, * p<0.1. Standard errors in parentheses.

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