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Product Innovation and Growth: The Case of Integrated Circuits

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Abstract

A puzzling evidence stemming from the applied research on growth and innovation is that successful innovations do not appear to have a significant effect on sales growth rates, at odds with the expectation that successful innovators will prosper at the expenses of their less able competitors. The present paper tests a research hypothesis claiming that the level of observation at which applied research is typically conducted hampers the identification of a significant association between innovation and sales growth rates. Exploiting a unique and original database comprising detailed information on product innovations by leading semiconductor companies, we find components commercialized in the nearest past to positively affect the stream of corporate revenues.

keywords: Firm Growth; Product Innovation; Semiconductor industry

1 Introduction

In recent years considerable effort has been made by economists to provide an integrated treatment of two strands of research that developed independently: 1) studies exploring the sources and economic consequences of technological change, and 2) empirical investigations dealing with emerging regularities in the size and growth rates distributions of firms. Stylized models have thus emerged (Dosi et al., 1995; Cohen and Klepper, 1996; Klette and Griliches, 2000; Klette and Kortum, 2004) that jointly address these issues deriving implications for both the performance of individual firms and the evolution of industrial structures. Along side, an increasing number of empirical studies examined the relationship between innovativeness and firm performance considering different types of models, estimation methods, measures of corporate performance and innovation activity (Geroski et al., 1997; Bottazzi et al., 2001; Del Monte and Papagni, 2003; Loof and Heshmatt, 2006). An intriguing evidence stemming from this stream of applied research is that successful innovations do not appear to have a significant effect on sales growth rates, at

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odds with the expectation that successful innovators will prosper at the expense of their less able competitors.

This puzzling evidence represents the starting point for the discussion in this paper[1]. We study how the propensity of firms to introduce incremental product innovations affects their rate of growth in a high-technology context, the integrated circuits (hereafter ICs) industry. In particular, we want to test a research hypothesis claiming that the level of observation at which applied research is typically conducted hampers the identification of a significant association between innovation and growth rates. This line of reasoning hinges on the idea that microsectors, defined as groups of relatively homogeneous products or technologies, rather than standard four digit industries, are the proper locus where processes of technological innovation and imitation affect firms' growth (Dosi et al., 1995). Accordingly, researchers should look into conventionally defined (four digit) industries so as to identify clusters of products that directly compete, and tackle the innovation-performance relationship at this narrow defined level of analysis.

The paper draws on a unique and original database comprising detailed information on sales figures and new products announcements for a representative sample of ICs producers. The uniqueness of our data stems from the fact that we have been able to disaggregate the information on sales and product innovations in eighteen, reasonably homogeneous, product segments. This allows us to tackle a major drawback of variables measuring innovative output. Those variables are, in fact, counts of innovations with non-equivalent technological and economic value that cannot be simply added one to another to obtain a concise indicator. Neglecting this kind of heterogeneity may bias inter-firms comparisons because the degree of innovativeness assigned to each of them is computed by algebraic summations of fairly disparate objects (Tether, 1998).

The rest of the paper is organized as follows. Section 2 introduces the key results of previous studies assessing the relationship between innovation activity and firm performance. It also discusses alternative hypotheses accounting for the non-significant association between innovative outputs and firm's growth rates. Section 3 provides descriptive statistics regarding the size, growth, and product innovation of sampled firms. Section 4 involves an econometric analysis of how product innovation affects growth at two level of observation, the corporate level and the business unit level. Section 5 concludes the paper.

2 Innovation and Growth: Background Literature

Logic dictates that innovation is a powerful explanatory factor behind differences in firms' performance, with companies that succeed in innovation prospering at the expense of their less able competitors. Indeed, evolutionary theories of economic change speculate that processes of technological innovation and imitation are major drivers of the relative performance of firms and the evolution of industrial structures[2] (Nelson and Winter, 1982). For a firm to survive in a context characterized by Schumpeterian competition simply

[1] An earlier version of this paper appears as "Quaderni di Dipartimento DISA, n 115" (Corsino, 2006)

[2] Notice how, in contrast with orthodox economics theory, this argument suggests that the relationship between industrial structures and degrees of innovativeness runs both ways.

producing a given set of goods, employing a given set of inputs and process technologies, is not enough. To be successful for a long period of time it must develop capabilities for innovation and to profit from innovation (Nelson, 1991). Different endowments of innovation capabilities, that is different stock of technological knowledge and diverse efficiencies in the search for innovations, will eventually lead to persistent differences in the economic performance of competing firms (Dosi, 1988). Thereafter, it can be convincingly presumed that there exists a stable association between the stock of innovative capabilities a firm owns, the output it produces and its economic outcomes. However, whilst the stock of knowledge and the underlying learning process through which it accumulates are unobservable, the appearance of product and process innovations can be regarded as a signal that valuable learning has occurred (Geroski and Mazzucato, 2002), and can be expected to account for performance differences across firms[3].

On the empirical ground, a quite robust evidence supports the idea that the estimated relationship between innovation and performance is sensitive, among other factors, to the way in which corporate performance and innovation activity are measured (Loof and Heshmatt, 2006). The former has been expressed either through market shares, accounting profits, market value, growth rates of sales, employees, and productivity. The latter has been proxied either by traditional indicators like R&D expenditures and patents counts, or using direct measure of the innovation output like product announcements in specialized trade journals, or the share of new products in a firm's total revenues.

If one is comfortable with believing that firms behave as profit maximizing agents, then accounting profitability becomes a natural summary statistics of corporate performance. Unfortunately, this indicator tends to understate performance differences across firms and it displays unusual patterns of variations when compared with other performance measures. On the contrary, growth rates of sales, employment and productivity exhibit a similar behavior and appear more reliable statistics to evaluate interfirm differences[4]. Their range of variation is large enough to ensure that drawing at random two companies away from the extreme values will reveal significant differences in performance. Moreover, unlike accounting profits, about 90% of the variation in growth rates is *within* variation which reflects changes in the performance of a typical firm over time (Geroski, 1998).

The measurement of innovation activities is problematic as well. Traditional indicators like R&D expenditures and patents counts, although extensively used in the literature, suffer from drawbacks that make their application questionable in several contexts (Pavitt, 1985; Kleinknecht, 1993). The "object" approach to innovation measurement (Archibugi and Pianta, 1996) and, more precisely, a literature-based innovation output indicator has become a valuable alternative to cope with such drawbacks. The metric, introduced at the beginning of the 1980s (Edwards and Gordon, 1984) and later applied in a broad range of empirical analyses (Coombs et al., 1996; Santarelli and Piergiovanni, 1996; Wakasugi and Koyata, 1997; Tether, 1998; Flor and Oltra, 2004), is a suitable indicator of innovative

[3]See Geroski and Mazzucato (2002, p. 628) for a formal analysis of the relationship between growth and learning by innovation.

[4]Studies dealing with employment growth rates typically aim at investigating the propensity to generate jobs of companies belonging to different size classes (Hart and Oulton, 1996), while the ones examining growth rates of sales go beyond an efficiency argument by taking into account how product market risks affect the successful introduction of innovative components in the marketplace (Barlet et al., 1998).

performance when one considers results for companies in terms of the degree to which they actually introduce inventions into the market (Hadgedoorn and Cloodt, 2003). Besides, it offers remarkable advantages over extant indicators (Kleinknecht et al., 2002): it provides a direct measure of the market introduction of new products or services; the data are relatively cheap to collect and since they are taken from published sources, their subsequent use is not hampered by privacy problems; it is possible to split the data by type of innovation, by degree of complexity or other dimensions; and finally, "the fact that an innovation is recognized by an expert or a trade journal makes the counting of an innovation somewhat independent of personal judgements about what is or is not an innovation"(Smith, 2005, p. 161).

The empirical research on firm growth and innovation activity pointed out some regularities that have been found stable across industries and along time (Klette and Kortum, 2004). On one hand, corporate growth rates appear very nearly random and can be reasonably approximated by Gibrat's Law (Geroski, 2005) according to which the "probability of a given proportionate change in size during a specified period is the same for all firms in a given industry - regardless of their size at the beginning of the period" (Mansfield, 1962, p. 1030). Nevertheless, exceptions to this conclusion exist. An increasing number of econometric studies suggest that a "mean reversion" process is at work in several contexts, with initial size and age exercising a transitory effect on corporate growth rates (Hall, 1987; Hart and Oulton, 1996; Oliveira and Fortunato, 2006). Similarly, recent studies drawing upon the tradition of stochastic models of firm growth (Ijiri and Simon, 1977) put forward that the observed distribution of growth rates departs from the expected Gaussian the Gibrat's Law would imply, but it rather displays a "tent-shaped" form (Stanley et al., 1996; Bottazzi et al., 2001). On the other hand, a loose relation between research intensity (or indicators based on patent counts) and sales or productivity growth has been typically found (Del Monte and Papagni, 2003). Furthermore, published works adopting an "object" approach to innovation indicators (Table 1) suggest that although a positive link between innovation output and level measures of firm performance generally exists, a significant effect of successful innovations on sales growth rates has not been generally identified.

Among the major contributions, Geroski et al. (1997) analyze a panel of 271 quoted UK firms for which data on major innovations and granted patents are available. None of these two sets of variables (in current and lagged values) has any impact over growth rates of firms, and excluding them from the model does not affect estimated coefficients of other variables. While one might suspect that this finding is an artifact of the short period over which the effect of innovations are measured, Geroski and Mazzucato (2002) show that it is not actually the case. The authors examine the link between product and process innovations introduced by US car manufacturers and their growth rates over a long period lasting from 1910 to 1998. Despite the evidence that lagged output is, to some extent, correlated with corporate growth, no significant effect of different measures of innovation arises. Bottazzi et al. (2001) provide further evidence on this point. Investigating a data set comprising information for the world largest pharmaceutical companies over an eleven years period, the authors find that neither the introduction of New Chemical Entities nor that of patented products affects a firm's growth performance[5].

This piece of evidence rises the crucial question of why it is not easy to find, on the empirical ground, any positive relationship between innovation and firms growth. The research hypothesis we investigate in this paper refers to the level of observation at which empirical analysis are typically conducted and suggests that the locus of learning, innovation, competition, changes in market shares is to be found at a much more disaggregated level of observation than standard four digit industries Dosi et al. (1995). "Microsectors", defined as groups of relatively homogeneous products or technologies, are the proper level where one has to examine the evolutionary conjecture according to which the processes of technological innovation and imitation are major drivers of firms' growth. Unfortunately, finding a suitable level of aggregation is not a simple task. Indeed, "even if we classify the industry's products into distinct categories associated with different technologies, we find that, for some groups of users, two product categories may be close substitutes, whereas for another group of users, they may be poor substitutes" (Sutton, 1998, p. 15). When dealing with variables measuring innovative output the proper identification of homogeneous groups of products becomes even more compelling. The major problem is that those variables are counts of innovations whose technological and/or economic value may differ a lot, therefore, they cannot be simply added one to another to generate a concise indicator. Neglecting this kind of heterogeneity implies that values of innovativeness assigned to each company are not directly comparable because computed by algebraic summations of fairly different objects.

A second hypothesis takes into account the degree of novelty of innovations, their nature (product *vs* process), and the economic environment the firm faces. The degree of product novelty may exercise two opposite effects on the stream of a corporate's revenues. On one side we might have an *inertia effect* according to which the greater the novelty the slower the market's acceptance of novel products over time. On the other side an *efficiency effect* might ensure a quicker acceptance of innovations satisfying a compelling market demand. The magnitude of the two effects likely depends on the technological opportunities characterizing each industry with "the *inertia effect* prevailing when there are little technological opportunities, while the *efficiency effect* prevailing when there are abundant technological opportunities" (Barlet et al., 1998, 459). Whilst the influence of incremental product innovations might be negligible in industries subject to rapid technological change, minor process innovations may be found more effective. For example, the cumulative effect of incremental improvements in manufacturing technology led Japanese producers of semiconductors to catch up with U.S. pioneers during the '80s (Rosenberg and Steinmueller, 1988).

Two further rationales may help understand why innovation has not been found to influence firm growth. The first line of reasoning, stemming from the empirical observation that all factors different from size typically have a modest impact on growth, argues that firms would expect their growth due to innovation limited by their existing size

[5]Recent contributions suggest that the above conclusions hold also in the services sector. Cainelli et al. (2006) work on a longitudinal firm-level database of Italian service companies, and once again they don't uncover any significant association between a set of innovation variables (including service innovation, product innovation, ICT expenditure per employee, R&D, design, know-how expenditures per employee) and growth rates. Loof and Heshmatt (2006) obtain analogous results for a panel of Swedish companies.

Table 1: Econometric studies of the effects of innovation output on firm performance

Author/year	Sector	Country	Innovation variable	Sales growth	Employment growth	Market share	Productivity	Export/sales	Firm survival	Financial variables
Mansfield, 1962	Steel & Petroleum firms	US	Major innovations	Positive relation						
Robinson, 1990	238 start-ups	US	Product innovations			Positive relation				
Geroski, 1991	3-digit industries	UK	Major innovations				Positive relation			
Kleinschmidt & Cooper, 1991	125 industrial firms	Canada	Product innovations			Positive relation				Positive relation
Geroski et al., 1993	721 quoted firms	UK	Major innovations							Positive relation
Banbury & Mitchel, 1995	Implantable cardiac pacemakers	US	Product innovations			Positive relation			Positive relation	
Cesaratto & Stirati, 1996	Manufacturing	Italy	Propensity to innovation	Unrelated	Unrelated		Unrelated	Positive relation		
Geroski et al., 1997a	271 quoted firms	UK	Major innovations	Unrelated						
Roper, 1997	Small firms	UK-D-IR	Propensity to innovation					Positive relation		
Crepon et al., 1998	Manufacturing	France	Propensity to innovation				Positive relation			
Tether & Massini, 1998	Small firms	UK	Propensity to innovation		Positive relation					
Blundell at al., 1999	340 manufacturing firms	UK	Major innovations							Positive relation
Roberts, 1999	Pharmaceutical industry	US	Propensity to innovation							Positive relation
Bottazzi et al., 2001	Pharmaceutical firms	World	Product innovations	Unrelated						
Llorca Vivero, 2002	Manufacturing	Spain	Process innovations				Positive relation			
Geroski & Mazzucato, 2002	Top car producers	US	Product/process innovations	Unrelated						
Geroski et al., 2002	640 firms	UK	Major innovations							Positive relation
Sharma & Lacey, 2004	Pharmaceutical industry	US	Product innovations							Positive relation
Loof & Heshmati, 2006	Manufacturing firms	Sweden	Propensity to innovation	Positive relation[a]						
Cainelli et al., 2006	735 service firms	Italy	Propensity to innovation	Unrelated			Positive relation			

[a] Loof and Heshmatt (2006) find a positive and significant impact of innovations new to the market on sales growth of manufacturing firms. Viceversa, they do not find any effect related to innovations new only to the firm. Likewise they don't find both types of innovations related to sales growth in the service sector.

(Cohen and Klepper, 1996). The latter would affect performance not only in a *direct* way, but also *indirectly*, by conditioning the impact of other explanatory factors (Geroski, 1998). The second argument originates from the empirical observation that whether major or incremental and whether patented or not, innovations are typically imitated in between one and three years, thus suggesting that rents due to innovation are quickly dissipated (Levin et al., 1987). Accordingly, it is commonly assumed that firms would expect to benefit from their innovation through increasing their price-cost margins rather than through higher growth rates (Cohen and Klepper, 1996).

The above discussion sets apart the major forces that may affect the sign and magnitude of the link between innovation activity and corporate growth. In this paper we assess whether carrying out empirical investigations at different levels of analysis significantly changes the estimated impact of product innovation on sales growth rates. We confine our analysis to a high-technology context, the integrated circuit industry[6], comprising relatively stable product segments. We start with a "corporate" level analysis presuming that integrated circuits are an homogeneous product and that their commercialization is the only business activity sampled firms are involved in. Thereafter, we consider an industry breakdown that allows us to identify eighteen distinct segments[7], each of them containing relatively homogeneous groups of products with peculiar functional technologies, average selling prices, ultimate applications, and sales dynamics. We define an individual "business unit" as a firm's activity within a given product segment (Rumelt, 1982; Gimeno and Woo, 1999). Accordingly, semiconductor producers in our sample may either consist of a single business unit or, alternatively, comprise several business units competing in distinct product segments.

To assess whether moving from a corporate to a business unit level of observation affects the estimated relationship between innovation and firm growth we have to control for other factors mentioned above. The limiting role of current size, as well as, costs associated with plant expansions does not seem to be a major concern in our setting for a couple of reasons. First, both integrated device manufacturers (firms that internally realize the production of components they sell) and *fabless* companies (firms that receive the majority of their finished wafer supply from specialized manufacturers) can outsource manufacturing services to external suppliers - *foundries* - thus lowering the share of total sales that must be re-invested in new capital. Second, as a consequence of the massive capital expenditures in the early 1990s, the industry has been experimenting a long wave of overcapacity that shields companies without internal facilities from the risk of not having access to production services (IC_Insights, 2004).

Limiting our attention to a single industry helps neutralize the confounding effect that patent protection may exercise on the innovation-growth relationship. Such an effect represents a major concern for intersectoral studies taking into account firms characterized by varying degrees of propensity to patent. Furthermore, previous research about the semiconductor industry emphasized that, although important, patents do not secure inno-

[6]Combining definitions provided in the U.S. 1997 Economic Census of Manufactures and the Gale Thompson's PROMT database, we identify the industry under study as a 5-digit SIC level industry (36741).

[7]See Appendix A for details about the breakdown of the integrated circuit industry employed in this paper.

vators from the risk associated with competitors imitation and the consequent dissipation of innovation rents. Results form the Yale Survey, an inquiry about appropriability conditions across a broad sample of manufacturing industries (Levin et al., 1987), for example, show an average effectiveness value of 4.5 points for product patents in the *semiconductors* industry, a higher value than the one calculated for process patents, but still lower than the effectiveness associated with alternative means of protection (e.g. lead time, learning curves and sales or service efforts).

In this study we deal with product innovations only. As a consequence, one can reasonably argue that the estimated relationship between innovation and corporate growth rates significantly depends on the degree of novelty of new devices commercialized. Unluckily, we do not have any additional information about new products apart from the year of introduction and the branding company. This lack of information prevents us from distinguishing, for example, components that are new to the firm but not to the market, from those that are new for both of them. Interviews with industry operators clarified that the type of product we're dealing with are *incremental* innovations, as we will discuss in the next section. Jointly considering this characteristics of our innovation data along with previous research suggesting that the *efficiency effects* prevails in industries subject to rapid technological change (Barlet et al., 1998), we would not be surprised of getting a non-significant association between incremental product innovations and corporate growth rates. Nevertheless, what we are primarily interested in is whether, and to what extent. shifting from the corporate to the business unit level of analysis changes the significance and magnitude of the estimated relationship.

3 Descriptive Analysis

3.1 The Data Set

The statistical analysis performed in this paper exploits a unique and original data set covering a sample of integrated circuit producers from all around the world. The uniqueness of our data set stems from the fact that we've been able to disaggregate the information on sales and product innovations in reasonably homogeneous clusters corresponding to those "microsectors" where learning, competition, and processes of technological innovation and imitation take place, according to evolutionary theories of industrial dynamics (Dosi et al., 1995).

We rely upon a taxonomy commonly used by research companies (iSuppli, IC Insights, Gartner Dataquest) to identify reasonably homogeneous groups of semiconductor products. The taxonomy is built around three major characteristics of integrated circuits: 1) their functional technology - IC components can be divided in analog and digital devices; 2) their degree of customization - ICs are classified as standard devices and custom devices; 3) the final application for which custom devices are tailored - communication infrastructures, computers, storage devices, consumer electronics, automotive and industrial systems. The resulting industry breakdown comprises eighteen clusters corresponding, by and large, to segments at the 7-digit SIC level[8].

[8]According to the Gale Thompson's PROMT database the Static Random Access Memory segment

The data set was built merging information on sales figures from the Competitive Landscaping Tool (2005) and the Strategic Reviews Database (2001, 2004) [9], with data on product announcements gathered from trade, engineering and technical journals accessible through multiple sources[10]. Since we're interested in the role of product innovation on incumbents' growth, we selected a balanced panel of ICs producers that were continuously active in the period 1998-2004. The matching procedure resulted in a sample of 95 companies[11] accounting for about the 80% of total integrated circuits revenues and representative of the population of integrated circuits producers[12].

3.2 Size Distribution

Integrated circuits revenues represent the total amount of semiconductor shipments for about the 70% of companies in our sample. They account for more than 70% of semiconductor revenues for the 90% of producers, while for almost the 8% of companies ICs revenues represent less than the 50% of their semiconductor production. Let $S_i(t)$ be the ICs sales of firm i ($i \in [1, \ldots, 95]$) at time t ($t \in [1998, \ldots, 2004]$), and define the business size of each producer as $s_i(t) = log(S_i(t))$[13]. Values reported in the upper box of Table 2 show that the ratio of the standard deviation to the mean as well as the skewness and kurtosis of $s_i(t)$ are nearly constant over time, implying a stable yearly distribution of $s_i(t)$

in our taxonomy would be associated with the product code 3674125, digital signal processors with the product code 3674129, and Microprocessors with the product code 3674124. See Appendix A for a description of the eighteen product segments.

[9] The *Competitive Landscaping Tool* is published by iSuppli, Inc., an electronics industry research company headquartered in El Segundo, California. The *Competitive Landscaping Tool* is a market share database enabling users who are interested in the global semiconductor industry to extract data of more than 240 companies, across more than 130 product segments, for the period 2001-2004. The *Strategic Reviews Database* is released by IC Insights, Inc., an integrated circuit market research company headquartered in Scottsdale, Arizona. Founded in 1997, IC Insights offers total analysis of the IC market, including current business, economic, and technology trends, the impact of new products on the market, company sales forecasts, capital spending trends, and other relevant IC industry information. The *Strategic Reviews* is a complete database of financial, strategy, product, technology, and fab facility information on more than 200 of the worlds leading IC manufacturers and fabless suppliers.

[10] They include the Gale Thompson's PROMT database, the Markets and Industry News database, the OneSource database, and press releases available on companies' web sites.

[11] Most of the companies not covered in our sample are located in Taiwan and China; for these producers new products announcements were unavailable either in trade and specialized journals, or on their Internet web sites. Other firms excluded are the ones mainly involved in the production of Application Specific Integrated Circuits (ASICs) - components designed and manufactured for the exclusive use of one customer - and few Japanese diversified companies for which internal transfers represent a significant fraction of their total IC revenues (e.g. IBM Microelectronics, Elmos, Sony and Sharp.)

[12] We compared the first four moments of the size distribution of companies in our sample with those of two larger samples of firms from the Competitive Landscaping Tool; an unbalanced panel with between 193 and 205 companies, and a balanced panel of 174 firms over the period 2001-2004. This elaboration is available from the author on request.

[13] We choose sales turnover as a measure of business size rather than any accounting-based measure for two reasons. First, previous research has shown that it is less affected by measurement errors than other commonly used measure of firm size (Geroski et al., 1997). Second, because some firms in our database were diversified in several end use products (e.g., Philips, Toshiba, Samsung) it was difficult to obtain accounting data reflecting firm's activity in the IC business.

along the period of analysis. The average size sharply increased in year 2000, when the industry topped its maximum historical value at 177 B US$. The year after the market experienced a slump of 33 percentage points that brought back the industry to the 1999 values; since then a smoother pattern of expansion describes the evolution of company size. The computed values of skewness tell us that the size distribution is slightly skewed to the right, while the possible deviations from a normal curve are associated with the low value of the kurtosis. However, borrowing from Hart and Oulton (1996) and Geroski (1998) who found similar values for a sample of 280 large quoted UK firms, we can conclude that a log normal would be a first, reasonable approximation of the size distribution of ICs producers.

Table 2: Descriptive statistics of size, growth and product innovation

	Year						
	1998	**1999**	**2000**	**2001**	**2002**	**2003**	**2004**
	Business size						
Mean	5.18	5.57	6.02	5.67	5.66	5.78	5.95
Standard Deviation	2.08	1.96	1.73	1.67	1.71	1.69	1.70
Coefficient of variation	0.40	0.35	0.29	0.29	0.30	0.29	0.29
Skewness	-0.30	-0.39	0.30	0.26	0.18	0.29	0.30
Kurtosis	3.41	4.51	2.21	2.36	2.34	2.35	2.41
	Business growth						
Mean		0.38	0.45	-0.35	-0.001	0.11	0.18
Standard Deviation		0.46	0.62	0.45	0.35	0.27	0.23
Skewness		1.77	4.84	0.71	0.29	0.93	-1.29
Kurtosis		10.31	34.75	3.79	6.55	5.84	9.28
	Product innovation						
Mean	9.57	11.92	12.34	13.28	14.06	13.31	13.20
Standard Deviation	11.02	12.81	14.00	14.53	17.26	14.43	15.53
Coefficient of variation	1.15	1.08	1.13	1.09	1.23	1.08	1.18
Skewness	2.14	1.55	2.15	1.86	2.75	2.43	2.64
Kurtosis	8.14	4.66	8.55	6.50	12.34	9.85	10.72

3.3 Growth

When compared with other measures of firm performance, corporate growth rates appear extremely variable and their variations are extremely difficult to predict. The descriptive analysis we conducted over the business growth of IC producers, defined as $g_i(t) = s_i(t) - s_i(t-1)$, bears out this piece of evidence. The middle box in Table 2 presents simple statistics for the distribution of growth rates that, unlike business size, does not appear stable over time. Computed values of skewness and kurtosis clearly deviate from the ones characterizing a normal distribution. The maximum sample growth rate, over the entire period of analysis, is 6.7 time larger than the mean, while for business size the maximum is about 1.8 times larger than the mean.

Applying the analysis of variance we have been able to decompose the variation in growth rates across firms, over time, into two components, "*between*" and "*within*" variation. The former reflects differences in firms which last over a period, thus identifying permanent differences between firms. The latter reflects variation in the growth of a typical firm over time, thus suggesting that transitory differences affect firm performance over time Geroski (1998). Computed values show that the 84% of variation in growth rates across firms and over time is "*within*" variation. Such a large value implies that only a small fraction of year by year differences in the growth rates of IC producers persists for more than one period.

3.4 Product Innovation

Data on product innovation make up a unique collection of new semiconductor devices commercialized during the period 1998-2004 by producers from all around the world. Personal interviews with industry operators clarified that the type of products which might get a press release (and therefore appear in our database) are: *(i)* a new product family, *(ii)* a new member of an existing family with a new feature, *(iii)* a new product with a substantial enhancement of existing features[14]. We know the part number associated with each component, a reference code that uniquely identify a given product among all those a producer offers, the name of the company that commercialized it and the year-month in which the product was announced. Besides, a brief description is also available that allows us to assign each component to one out of the eighteen product segments in our taxonomy.

Descriptive statistics (lower box in Table 2) show that the average number of products per firm grew from 9.57 in 1998 to 14.06 in 2002, followed by a slight decline the years after. Along the same period the deviation around the mean increased whereas the coefficient of variation was stable around 1.1. Computed values of the skewness suggest that the distribution of product announcements is right skewed meaning that most firms introduce few components while a very small number of producers account for a large fraction of the innovation output that we observe. The median of the distribution is lower than the mean and ranged from a minimum of 5 in 1998 to a maximum of 9 in 2003. Computed values of the first and third quartiles tell us that the 25% of companies released at most 4 new product announcements, while the 75% of them recorded about 17 announcements during the seven years.

The classification of integrated circuits by product segments allows us to deepen our investigation. We find that none of the firms in our sample introduced new components in all the eighteen sub-markets, while eighteen firms (19%) announced new products in one segment only. Among the sampled firms, the 52.6% introduced new devices in at most three segments and the 89.5% innovated in less than ten, thus providing support for the idea that ICs producers tend to specialize rather than diversify their portfolio of activities. Only eight companies compete in ten or more segments and five of them ranked among the first ten IC vendors in 2004. Pairwise correlation coefficients of 0.6 and 0.7, respectively, suggest that a positive link exists between the average firm size and

[14]Products for which IC producers do not generally issue a press release are: (i) an existing product in a new package, (ii) an existing product with incremental changes in features.

the number of new product announcements, and between the average firm size and the number of product segments where a firm operates[15].

4 Econometric Analysis

The econometric analysis is organized in two stages. We start investigating the impact of a firm's innovativeness over its global growth performance, thus assuming integrated circuits as an homogeneous product and looking at the ICs business as a whole. Subsequently, we split sales figures and product announcements of each company by its constituting business units and explore the innovation-growth relationship at a finer level of analysis. According to previous research (Del Monte and Papagni, 2003; Oliveira and Fortunato, 2006) the analysis in both stages proceeds as follows: firstly, we test Gibrat's Law in order to asses whether current size should enter the model describing the evolution of growth rates and, after that, we augment the baseline model so as to verify whether incremental product innovations enhance the growth performance of ICs producers.

4.1 Innovation and the Corporate Growth Performance

We begin our exploration with a classical benchmark in the empirical literature, the relationship between size and growth of the firm (Sutton, 1997). This stream of research compares the null hypothesis that growth rates are random, hence can be well represented by Gibrat's Law, against the alternative that "mean reversion" induces a convergence in firm sizes over the long run. The empirical literature typically concentrate on the following model:

$$s_{i,t} = \alpha_i + \beta_i s_{i,t-1} + \epsilon_{i,t} \tag{1}$$

where $s_{i,t}$ is the logarithm of firm size at time t, $s_{i,t-1}$ is the value of size lagged one period, and the slope parameter (β_i) captures the effect of initial size on the growth rate. Two issues arise when such a model is at stake. First, if heterogeneities in the steady state sizes, or in the speed of convergence of firms are neglected (i.e. assuming $\alpha_i = \alpha, \quad \forall i, \quad \text{and } \beta_i = \beta, \quad \forall i$), then one may get biased estimates of the degree of convergence (Geroski et al., 2003). The availability of panel data sets mitigates this kind of problem by properly accounting for heterogeneity across firms. Second, the disturbance term in Eq. (1) might be serially correlated because of persistence of chance factors which make a company grow abnormally fast or abnormally slowly. The presence of serial correlation induces dependence between the lagged dependent variable $s_{i,t-1}$ and $\epsilon_{i,t}$, thus generating inconsistent estimates of β in typical panel data with large N and small T (Chesher, 1979).

Departures from Gibrat's Law arise when the null hypothesis H_0: $\beta_i = 1$, is rejected in favor of the alternative H_1: $\beta_i < 1$. The latter signifies the existence of "mean reversion",

[15] It is worth to notice that three leading semiconductor companies, Intel Corp., Infineon Technologies, and Advanced Micro Devices, specialize in few product classes, despite their size. Whether innovation is also associated with higher growth rates is the central theme of the next section.

implying that small firms in period t will grow in $t+1$ faster than larger ones[16]. In this case, if $\alpha_i > 0$, firms will converge to different steady states sizes, equal to $-\alpha_i/\beta_i$, even within the same industry[17]. A concern when using microeconomic panel data sets is that some estimators of autoregressive models like Eq. (1) do not identify the parameter of interest when the time series in not stationary. To cope with such a problem, unit root tests have been proposed since the early 1990s (Maddala and Wu, 1999) "driven by the hope that inference about stationarity and cointegration can be made more straightforward combining information from the time series dimension with that obtained from the crosssectional" (Banerjee, 1999). Borrowing from this literature we apply the methodology developed by Im et al. (2003) to test for the presence of a unit root in the business size series in our sample. The testing procedure assumes a slightly different version of equation (1) with the stochastic process generating $s_{i,t}$ modeled as:

$$s_{i,t} = (1 - \beta_i)\alpha_i + \beta_i s_{i,t-1} + \epsilon_{i,t} \tag{2}$$

The above specification reveals that there is no fixed effects under the null, while under the alternative of "mean reversion" each fixed effect is equal to $(1 - \beta_i)\alpha_i$. The test is particularly appealing for our study because it considers a formulation of the alternative hypothesis that allows for heterogeneity across groups. In fact, while the null hypothesis remains H_0: $\beta_i = 1$, the alternatives become

$$H_1 : \beta_i < 1, \quad i = 1, 2, \ldots, N_1, \qquad \beta_i = 1, \quad i = N_1 + 1, N_1 + 2, \ldots, N$$

implying that some of the β_is are less then one. This approach views the panel structure as a system of N regressions, and computes the standardized $\hat{t}$-bar statistics, $Z_{\hat{t}bar}$ combining the Student's *t-tests* obtained from Dickey-Fuller (DF) regressions on the data of each firm. Im et al. (2003) show that under the null hypothesis H_0: $\beta_i = 1$ the standardized $\hat{t}$-bar statistics is asymptotically distributed as a $N(0, 1)$ with exact critical values for different combinations of N and T. Using data for ICs producers in the working sample, over the period 1998-2004, we obtain a $Z_{\hat{t}bar}$ equal to -3.046, a value that falls outside the acceptance region of the null at a significance level of the 1%. Summarizing. The empirical investigation we undertook shows that Gibrat's Law does not hold in our sample[18]. Accordingly, we must enter current size as an explanatory variable in the model describing the growth rate of the firm.

Given the foregoing piece of evidence, the baseline specification of our model is further augmented by including a one-year lag of the dependent variable together with a set of

[16]The case $\beta_i > 0$ is typically excluded because it would imply diverging firm sizes, meaning that large firms will grow faster than smaller ones, and will therefore become even larger.

[17]However, even if the null hypothesis is not rejected, Gibrat's Law may fail because: *(i)* the error term in equation (1) is autoregressive ($\epsilon_{i,t} = \rho\epsilon_{i,t-1} + \nu_{i,t}$), so that above average growth in a period tends to last also the year after ($\rho > 0$), or tends to be followed by a period of below average growth ($\rho < 0$); *(ii)* the standard deviation of growth rates varies with firm size, that is when the fitted residuals in Eq. (1) exhibit heteroscedasticity, $\sigma^2_\epsilon = \sigma^2_\epsilon(i, t)$ (Goddard et al., 2002).

[18]We obtained the same results performing the test over a subset of 85 companies with sales figures available for nine continuous years. Furthermore, we didn't find any evidence of an exact unit root when running standard estimation technique on *Eq.* (1).

regressors capturing the influence of product innovation over rates of growth. We specify the following regression equation:

$$\Delta s_{i,t} = \rho \Delta s_{i,t-1} + \gamma s_{i,t-1} + \theta(L) I_{i,t} + \alpha_i + \lambda_t + \nu_{i,t} \tag{3}$$

where $\Delta s_{i,t}$ is the rate of growth of the ICs business from year *t-1* to year *t*, and $s_{i,t-1}$ is the lagged business size that is expected to negatively affect current growth by a factor γ. The dynamic specification in Eq. (3) includes the lagged dependent variable, $\Delta s_{i,t-1}$, which captures the effect of growth in previous years on contemporaneous performance through the parameter ρ. The term $\theta(L)$ is a polynomial in the lag operator L, and the variable $I_{i,t}$ measures the total number of product announcements at the end of each year. The regression equation also includes a firm-specific effect, α_i, that accounts for time-invariant heterogeneity across firms, and a time-specific effect, λ_t. The disturbances $\nu_{i,t}$ are assumed identically and independently distributed.

Table 3 presents estimated coefficients associated with explanatory variables included in the econometric model. We report OLS and Differenced GMM estimates for mere comparison. We will not comment on them due to finite sample biases they suffer in short panels with persistent time series and individual fixed effects (Bond, 2002). We instead concentrate on System GMM estimates (Arellano and Bower, 1995; Blundell and Bond, 1998) reported in the other two columns of the table. Diagnostic statistics (*m1* and *m2* tests) suggest that the pattern of autocorrelation in the differenced residuals of the GMM estimates (significant negative first order serial correlation in $\Delta \nu_{i,t}$, but not significant second order serial correlation) is consistent with the assumption that the $\nu_{i,t}$ disturbances in Eq. (3) are serially uncorrelated. Furthermore, the Hansen test for the validity of instruments used suggests that the model is correctly specified and the computed coefficients are consistent (Bond, 2002).

When looking at the estimated parameters we notice that the coefficient associated with lagged size is negative (above -0.15) and statistically significant at the standard 5% level, implying that a "mean reversion" process makes small companies growing faster than larger ones. Conversely, growth experienced in the previous period has a positive and statistically significant effect on current growth performance. The number of new product announced in the current year, along with two lags of this variable, are meant to capture the effect of corporate "innovativeness" over its sales growth rates. Although relatively short, the lags structure we're dealing with sufficiently covers a time span that lasts until the decline stage in the life cycle of a typical semiconductor components (ICE, 1999). A concern with the regressor $I_{i,t}$ is whether it has to be treated as an endogenous variable rather than a predetermined one[19]. A difference Hansen statistics that specifically tests the additional moment conditions used in the first-differenced equation for period t, supports the idea that $I_{i,t}$ can be treated as a predetermined variable[20]. Whether the

[19]Maintaining that the $\nu_{i,t}$ disturbances are serially uncorrelated, a generic $x_{i,t}$ series may be endogenous in the sense that $x_{i,t}$ is correlated with $\nu_{i,t}$ and earlier shocks, but $x_{i,t}$ is uncorrelated with $\nu_{i,t+1}$ and subsequent shocks; predetermined in the sense that $x_{i,t}$ and $\nu_{i,t}$ are also uncorrelated, but $x_{i,t}$ may still be correlated with $\nu_{i,t-1}$ and earlier shocks (Bond, 2002).

[20]This piece of evidence is in line with previous research which does not find any significant relationship between firm growth and subsequent innovation rates for firms in high-technology environments (Audretsch, 1995; Klomp and Van Leeuwen, 2001) This is because companies in high-technology indus-

Table 3: Determinants of Growth at the Corporate Level

Dependent Variable: $Growth_{i,t}$				
	OLS levels	GMM DIFF	GMM SYS (1)	GMM SYS (2)
$Growth_{i,t-1}$	0.1946	0.086	0.1534	0.1534
	(5.90)	(2.00)	2.33	(2.32)
$Size_{i,t-1}$	-0.0294	-0.5063	-0.1509	-0.1420
	(-3.19)	(-3.81)	-2.41	(-2.36)
$Innovation_{i,t}$	0.0015	0.0083	-0.0029	0.0020
	(0.91)	(0.88)	(-0.60)	(0.99)
$Innovation_{i,t-1}$	-0.0012	0.0027	0.0021	0.001
	(-0.59)	(0.67)	(0.73)	(0.53)
$Innovation_{i,t-2}$	0.0013	0.0047	0.0049	0.0046
	(0.63)	(1.24)	(2.91)	(2.31)
Time dummies	Sig.	Sig.	Sig.	Sig.
Constant	-0.272	-0.59	1.188	1.095
	(-3.63)	(-8.95)	3.37	(3.07)
Observations: $N \times T$	380	380	380	380
R^2	0.33			
m1		-1.76	-2.49	-1.97
m2		-0.15	-1.44	-1.21
Hansen test		0.20	0.39	0.29
Dif-Hansen				0.127

1. In parenthesis are Student's t-test values. Standard errors asymptotically robust to heteroscedasticity are considered.

3. m1 and m2 are tests for first-order and second-order serial correlation, asymptotically N(0,1). They test the levels residuals for first-differenced residuals from GMM estimates.

4. GMM DIFF results are one-step estimates. GMM-SYS estimates are in the two-step version.

5. Hansen is a test of overidentifying restrictions for the GMM estimators, asymptotically χ^2. P-value is reported.

6. Dif-Hansen tests the validity of the extra moment conditions available when $Innovation_{i,t}$ is treated as a predetermined variable rather than an endogenous one. P-value is reported.

variable accounting for current period innovation is treated as a predetermined regressor or not, we find that only product announcements dated *t-2* have a positive and significant effect (0.5%) on the growth performance of the firm. We will shortly comment on both the magnitude of the estimated innovation coefficients and the finding that only past product announcements seem to positively affect the firm's growth. Before doing that, however, we want to ascertain whether, and how, the foregoing pieces of evidence changes when shifting to a finer level of observation, the business unit level.

tries are already in high growth environments. In fact, if the firm's rate of growth has previously been slow, a manager will place even more value on innovative strategy, since the poor growth performance is likely to be attributable to the type of products currently being offered by the company.

4.2 Innovation and Growth at the Business Unit Level

Firms operating in the integrated circuits industry embody bundles of products characterized by varying degrees of sales dynamics, average selling price, product life cycle, device complexity, etc. In this study we rely on an industry taxonomy that allows us to identify eighteen clusters of relatively homogeneous components referred to as product segments. Accordingly, we define an individual "business unit" as a firm's activity within a given product segment (Rumelt, 1982; Cohen and Klepper, 1996; Gimeno and Woo, 1999). The Competitive Landscaping Tool database gives us information about ICs sales for business units belonging to all companies in the working sample. Therefore, matching sales figures of an individual unit with corresponding data on product announcements makes it possible to explore the relationship between innovation and growth performance at a fine-grained level of analysis, a feature that distinguish our contribution from previous research.

The database used in this section is indexed by firm, product segment and year. Specifically the index i identifies companies ($i \in [1, \ldots, 95]$), the index j identifies product segments ($j \in [1, \ldots, 18]$), and the index t identifies time ($t \in [2001, \ldots, 2004]$)[21]. The couple of subscripts ij identifies an individual business unit belonging to firm *i-th* and operating in sub-market *j-th*. With a complete panel we would have 1710 observations. In practice not all firm-product segment combinations are available because firms do not compete in every sub-market. We define active business units the ones that record positive sales in the Competitive Landscaping Tool database. Besides, we keep in our sample only units which were continuously active during the period 2001-2004[22]. After this cleaning procedure we are left with a working sample comprising 372 units observed over four years.

We start with investigating whether growth rates behaves according to Gibrat's Law of proportionate effects at this finer level of analysis. To this end we model the size evolution of a business unit through the following stochastic process:

$$s_{ij,t} = (1 - \beta)\alpha_{ij} + \beta s_{ij,t-1} + \epsilon_{ij,t} \tag{4}$$

where $s_{ij,t}$ is the logarithm of the *ij-th* business unit's sales at time t, $s_{ij,t-1}$ is the one period lagged value of the same variable and the slope parameter β captures the effect of initial size on the growth rate. Because of the short number of periods available, several procedures devised to test for the presence of a unit root can not be immediately used in our framework. To cope with this problem we apply a simple *t-test* proposed by Bond et al. (2005) and based on the OLS estimator of β in Eq. (4):

[21]The Competitive Landscaping Tool database does not provide sales figures disaggregated by product segments for years before 2001. Because of the reduced number of years available, comparisons between findings in this part of the study with those obtained in the previous section must be done with cautiousness.

[22]Indeed, a non trivial process of entry and exist from specific sub-markets took place in the industry. We recorded 39 companies (41%) entering or leaving at least one sub-market, with 25 cases of entry and 38 cases of exit.

$$t_{OLS} = \frac{\hat{\beta}_{OLS} - 1}{\sqrt{\widehat{Var}(\hat{\beta}_{OLS})}}$$

Under the null, $\beta = 1$, t_{OLS} has an asymptotic standard normal distribution as $N \rightarrow \infty$ for fixed T[23]. Monte Carlo experiments (Bond et al., 2005; Hall and Mairesse, 2005) show that this test may actually well perform when dealing with micro-data panels. OLS estimates of Eq. (4), while correcting for autocorrelation and within group heteroscedasticity, return a parameter β equal to 0.992. Using this estimated coefficient we compute a t_{OLS} statistics of -0.9, a value falling in the acceptance region of the null hypothesis, thus suggesting that past size doesn't affect current growth when working with disaggregated data. Accordingly we take a step forward modeling the relationship between growth and product innovation as follow:

$$\Delta s_{ij,t} = \theta(L) I_{ij,t} + \alpha_i + \lambda_t + \nu_{ij,t} \tag{5}$$

The specification in Eq. (5) differs from the one adopted in the previous section not only because the variable catching the effect of past size is excluded. We abandon the dynamic specification so far considered[24] and include in the estimated equation only variables measuring product innovation along with parameters controlling for firm and time specific effects. We do not enter any variable for unobserved effects at the business unit level for two reasons. First of all, the specification in Eq. (4) implies that this type of heterogeneity depends on the parameter β and it vanishes when this latter is equal to one, the case we are facing. Secondly, components that we treat as distinct product segments may in reality be organized under a unique division in a given firm. This implies that unobserved, time-invariant individual effects may be expected to exist at the firm level rather than being associate with individual business units. Such an assumption has two important consequences: *i)* we can work with data in levels, a non-trivial benefit given the short panel accessible; *ii)* we can enter further lags of the innovation variable thus capturing persistent effects of sustained incremental innovation over time.

Table 4 reports estimated coefficients under three alternative specifications of the regression model in Eq. (5). The first one presents pooled OLS estimates when only time effects are included in the model. It appears that contemporaneous product announcements and those occurred in the nearest past are, respectively, associated with a growth rate of 1 and 0.8 percentage points in the turnover of a given business unit. Nevertheless, the small R^2 suggests that differences in product "innovativeness" of firms explain only a marginal fraction of the observable heterogeneity in firm performance, a conclusion emphasized also in previous research (Geroski et al., 1997; Klomp and Van Leeuwen, 2001).

[23]Bond et al. (2005) argue in favor of this test stressing that consistent tests of the unit root hypothesis require consistent estimation only under the null. Under the alternative, $\beta < 1$, the OLS estimator is biased upwards, more so when the variance of α_{ji} is large relative to the variance of $\epsilon_{ji,t}$.

[24]The choice of not including a lagged value of the dependent variable as an additional regressor is supported by the computed value of the Wooldridge test (reported at the bottom of Table 4) which does not reject the hypothesis of no serial correlation in the error term of Eq. (5).

Table 4: Determinants of Growth at the Business Unit Level

Dependent Variable: $Growth_{ij,t}$			
	(1)	(2)	(3)
$Innovation_{ij,t}$	0.01	0.007	0.006
	(2.26)	(1.38)	(1.19)
$Innovation_{ij,t-1}$	-0.004	-0.006	-0.006
	(-0.82)	(-1.21)	(-1.34)
$Innovation_{ij,t-2}$	0.008	0.008	0.007
	(2.05)	(2.00)	(1.85)
$Innovation_{ij,t-3}$	-0.003	0.0002	-0.0002
	(-0.54)	(0.03)	(-0.04)
$Innovation_{ij,t-4}$	-0.006	-0.0004	0.0008
	(-1.54)	(-0.09)	(0.19)
Firms dummies		Sig.	Sig.
Sub-markets dummies			Not Sig.
Time dummies	Sig.	Sig.	Sig.
Constant	-0.05	-0.06	-0.17
	(-1.95)	(-1.39)	(0.90)
Observations: $N \times T$	1116	1116	1116
R^2	0.03	0.16	0.20
Wooldridge test	0.44		
	(0.51)		
Durbin-Wu-Hausman test	0.049		
	(0.82)		

1. In parenthesis are Student's t-test values. Standard errors are asymptotically robust to heteroscedasticity.

2. Wooldridge test detects first-order autocorrelation in the disturbance term. The null is no serial correlation; *P-value* in parenthesis.

3. Durbin-Wu-Hausman tests the endogeneity of the regressor *Innovation*; *P-value* in parenthesis.

To account for the existence of time-invariant effects at the corporate and product segment level we augment the model by entering both firm and sub-markets dummies; in doing this we are close to, but not quite, estimating a panel data model with fixed business unit effects. *F tests* on the significance of the two groups of dummies suggest that while firm effects are jointly distinguishable from zero, sub-market effects are not[25]. Although the introduction of firm dummies significantly improve the explanatory power of the model, causing the R^2 to rise until 0.16, the fraction of explained variation in the dependent variable is still small. In the model with firm dummies only, the magnitude of the coefficient associated with contemporaneous product announcements shrinks and its significance drops under the conventional level. Conversely, the contribution to growth

[25] In Model 2 the F test on the group of firm dummies gives a value of 3.57. In Model 3 F tests on the groups of firm and sub-market dummies give values of 2.88 and 1.57 respectively. This implies that the former are jointly distinguishable from zero, while the latter are not.

performance of devices commercialized in the nearest past remains stable.

To summarize. Although incremental product innovations may not be expected to significantly improve the growth performance of firms operating in industries subject to rapid technological change (Barlet et al., 1998), the econometric analysis carried out in this section tells us that marginal increments actually matter. Product announcements released in the nearest past seem to have a positive effect over growth rates at the corporate level as well as at the business unit level. This result supports the idea that incremental innovations affect a firm's ability to sustain its market position (Rosenberg and Steinmueller, 1988) by leveraging the capabilities to innovate that accumulate through the learning process (Geroski and Mazzucato, 2002) and the increases in productivity that the development of process and product innovations may bring about (Crepon et al., 1998).

Despite the statistical significance of the estimated coefficients, one may question whether their magnitude is to some extent negligible and why only past innovations impact the growth performance of sampled firms. With respect to the first point we want to stress that only two studies, out of those we reviewed, estimated a positive relationship between innovation and growth. Mansfield (1962) computed an average effect of major innovations on a firms growth rate ranging from 4% to 13%, whereas Loof and Heshmatt (2006) found that only innovations new to the market have a positive effect on a firms growth rate that is equal to 7.1 percentage points. Bearing in mind these results and considering that we only dealt with incremental innovations, without distinguishing components according to their degree of novelty, an average 0.5% effect of innovations on a firm growth rate does not actually seem irrelevant. Furthermore, in accordance with our research hypothesis, we obtain a higher estimated coefficients, 0.8%, when shifting from the corporate to the business unit level of analysis. We think that the significant impact of new products announced at time *t-2* is not surprising either. Indeed, product announcements, used in this paper as a proxy of "innovativeness", typically refer to products in the sampling stage which, in turn, precedes the production stage of approximately three months. Jointly considering this characteristics of our innovation data and the observation that revenues of a generic semiconductor product usually peak during the second year after its commercialization (ICE, 1999), our results become less ambiguous than they initially appeared.

5 Conclusions

While logic dictates that innovation is a powerful factor behind individual firm's fate and dynamics of industrial structures, a quite robust empirical evidence suggests that the estimated relationship between innovation and firm performance is sensitive to different factors like data sources, estimation methods, and the way in which corporate performance and innovation activity are measured (Loof and Heshmatt, 2006). Previous studies (Geroski et al., 1997; Bottazzi et al., 2001; Geroski and Mazzucato, 2002) employing sales growth rates as a measure of firm performance and adopting an "object" approach to innovation indicators have not usually found a significant association between successful innovations and corporate growth rates.

In this paper we pointed out four rationales that may account for the piece of foregoing evidence. A first hypothesis argues that, because firms embody rather idiosyncratic bundles of products, the level of observation (4-digit SIC level) at which empirical analysis are typically conducted is not the proper locus to track processes of learning, innovation and competition(Dosi et al., 1995). A second hypothesis suggests that the degree of novelty of innovations may exercise opposite effects on the stream of a corporate's revenues because the market's acceptance of novel products changes with the economic environment the firm operates in (Barlet et al., 1998). A third line of reasoning, stemming from the empirical observation that all factors different from size typically have a modest impact on growth, argues that firms would expect their growth due to innovation limited by their existing size (Cohen and Klepper, 1996). A final argument, originating from the empirical observation that whether major or incremental and whether patented or not, innovations are quickly imitated (Levin et al., 1987), claims that firms would expect to benefit from their innovation through increasing their price-cost margins rather than through higher growth rates (Cohen and Klepper, 1996).

In this study we concentrated on the first hypothesis and assess whether empirical investigations conducted at different levels of analysis yield significantly different estimates of the innovation-growth relationship. Moreover, the remark that literature-based innovation indicators tend to disregard technological and economic differences in the value of counted innovations (Tether, 1998) offers an additional underpinning for our work. The neglect of this type of heterogeneity, in fact, might bias the computed rate of innovativeness in such a way that fairly accurate inference can be drawn from interfirm comparisons [26]. Our exploration is based upon a unique database comprising information on sales figures and new product announcements for a balanced panel of firms operating in the integrated circuit industry. Employing a standard taxonomy of semiconductor components, we've been able to arrange the data in eighteen clusters of relatively homogeneous products, a feature that distinguish our contribution from previous research in the field. Thereafter, we carried out an econometric analysis aimed at measuring the impact of product innovation on both the global growth performance of ICs producers and the growth performance of their constituting business units.

In line with previous research (Geroski, 2005), corporate growth rates appear extremely difficult to predict. At the aggregated corporate level, incremental innovations introduced in the nearest past seems to significantly, although marginally, affect (0.5%) the growth performance of ICs producers. At the same time, a "mean reversion" process drives the evolution of the global corporate size, while positive effects associated with past growth performance persist, at leas in the short run. The econometric analysis performed at the business unit level supports the hypothesis advanced in this study; the influence of incremental product innovations on the focal unit growth is higher than the one recorded at the corporate level. ICs components commercialized in the nearest past account for an almost one percent increase in sales, although they explain only a small portion of growth rates variation.

The empirical investigation carried out in this paper can be extended along two di-

[26]Tether (1998), for example, shows that the normally unstated assumption of equivalent economic value in innovations may be misguiding and the conclusions relating innovativeness and firm size may dramatically change when it is taken into account.

rections. First of all, we may want to assess whether products characterized by an higher degree of novelty have a major impact on growth rates than minor innovations, in an industry with abundant technological opportunities. Secondly, we may examine how the introduction of new components by competitors in each sub-markets affects the performance of the focal firm, and whether positive spillovers from innovations in adjacent sub-markets exist.

A Product Segments Description

Amplifier/Comparator. Both Amplifiers and Comparators are high gain, general purpose, linear circuits. An amplifier provides voltage or current gain where the output is an amplified reconstruction of the input. Comparators are high gain amplifiers used in an "open-loop" configuration to provide a two-state (binary) output that identifies which of two analog signals is higher.

Voltage Regulator/Reference. Voltage regulators provide a regulated (normally unchanging) output voltage despite supply voltages and load current changes. Voltage references maintain a constant output voltage but are used for "reference" comparison.

Data Conversion Circuit. Data Converters convert between analog and digital domains. Data Converters can be 6 bits or 24 bits or any resolution in between, the higher resolution giving finer granularity.

Interface. This general-purpose, mixed-signal device serves as an interface between an electrical system/component and other external systems/components, whether electrical or nonelectrical.

DRAM. Dynamic Random Access Memories are volatile memory ICs that lose their contents when power is lost and whose contents are simply overwritten with new information. DRAMs have a single-transistor memory cell.

SRAM. Static Random Access Memories are volatile memory ICs with a minimum of four transistors per memory cell.

Flash Memory. Flash Memories are nonvolatile memory ICs that retain their contents when power is lost and requires an erasing cycle before storing new data. Flash memories have single-transistor or multitransistor memory cells and sector or block (not byte) erasing.

Other Memory. Other Memory ICs include all other memory not already accounted for in the DRAM, SRAM, flash Memory categories.

MPU. MPUs are digital logic devices that have an undefined output function but are capable of operating on a sequence of instructions from a stored program to produce the desired output.

MCU. MCUs are digital ICs designed for stand-alone operation that includes a programmable processing unit, program memory, read/write data memory and special input/output (I/O) capability.

DSP. DSPs are programmable digital ICs designed for stand-alone operation, constituting a high-speed arithmetic unit (typically Multiply Accumulate [MAC]) designed to perform complex mathematical operations, such as Fourier transforms in real time to generate, manipulate or interpret digital representations of analog signals.

Standard Logic. Standard Logic refers to commodity family logic with fewer than 150 gates; it is sometimes referred to as glue logic.

PLD. A PLD is a logic device that can be adapted to a specific logic function by programming the logic configuration.

Display Driver. Display Drivers are devices that drive an electronic imaging device to provide an information interface.

ASIC/ASSP - Consumer. Application Specific Integrated Circuits sold to one or more customer for a consumer application. Consumer applications include video, audio, interactive products, personal electronics and appliances.

ASIC/ASSP - Communication. Application Specific Integrated Circuits sold to one or more customer for an application in wired or wireless communications. Such an application could be cable modem CPE, cable modem headend equipment, central office line cards/system cores, cellular phones, wireless phones, cordless telephones or mobile infrastructure equipment.

ASIC/ASSP - Compute & Storage. Application Specific Integrated Circuits sold to one or more customer for a compute or storage application. Compute applications include computers, monitors and printers. Storage applications include rigid disk drives, optical disk drives, tape drives, DAS/FAS and storage network infrastructure.

ASIC/ASSP - Industrial & Other. Application Specific Integrated Circuits sold to one or more customer for an an application in industrial, medical automotive or other applications not specifically characterized previously.

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