Product Innovation and Growth: The Case of Integrated Circuits

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Abstract

Applied research on growth and innovation seems to suggest that successful innovations do not significantly enhance firm growth. This paper tests the hypothesis that the level of observation at which applied research is typically conducted hampers identification of a significant association between innovation and sales growth rates. Exploiting a unique data set, we find that product innovations commercialized in the immediate past positively affect the corporate revenue streams of semiconductor companies.

keywords: Firm Growth; Product Innovation; Semiconductor industry

JEL Classification: L25, L63, O31

Introduction

In recent years, an increasing number of empirical studies has examined the relationship between innovativeness and company 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). What is puzzling in this stream of applied research is that successful innovations do not appear to have a significant effect on the growth rate of sales, which contrasts with a body of that theoretical literature which suggests that there is a close link between innovation and growth (Nelson and Winter, 1982; Aghion and Howitt, 1992; Klette and Griliches, 2000; Klette and Kortum, 2004).

This is the starting point for the discussion in this paper. 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 (IC) industry. In particular, we test the research hypothesis that the level of observation at which applied research is typically conducted hampers the identification of a significant association between innovation and firm growth rates. This line of reasoning hinges on the conviction that submarkets[1] within conventional four digit SIC (Standard Industry Classification) code industries are the proper locus for the processes of technological innovation and imitation to affect firm growth (Dosi *et al*., 1995). Submarkets can be defined as clusters of relatively homogeneous products that draw on a similar knowledge base, use a common production technology and target the same customer group (Sutton, 1998). Thus, the innovation-performance relationship should be examined at this narrowly defined level of analysis.

We construct a unique and original database comprising information on sales figures and new product announcements for a representative sample of IC producers. Our data are unique and are based on disaggregated information on sales and product innovations in 18 market segments. This allows us to gauge the impact of product innovation on revenue growth at the corporate level, assuming that IC are a homogeneous product and represent the only goods that firms commercialize. Moreover, it allows us to estimate the innovation-growth relationship at the level of the individual business unit, which distinguishes this contribution from previous research (Cesaratto and Stirati, 1996; Geroski *et al*., 1997; Cainelli *et al*., 2006). The availability of data at business unit level provides a unique opportunity to address a shortcoming of the variables currently used to measure innovative output, i.e. counts of innovations of non-equivalent technological and economic value, that cannot be simply added up to obtain a concise indicator. Overlooking this type of heterogeneity could bias inter-company comparisons because the degree of innovativeness assigned to each of them is figured using algebraic summations of fairly disparate objects (Tether, 1998).

The paper is organized as follows. Section 2 introduces key results from previous studies on the relationship between innovation activity and firm performance. It discusses alternative hypotheses on the non-significant association between innovative outputs and company growth rates. Section 3 provides descriptive statistics regarding the size, growth and product innovation of sample firms. Section 4 presents the results of the econometric analysis on the effects of product innovation on growth at two levels of observation: corporate and business unit. Section 5 concludes the paper.

1 Innovation and Growth: Background Literature

Logic dictates that innovation is a powerful factor behind differences in firms' performance, with companies that innovate successfully 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 structure (Nelson and Winter, 1982). For a firm to survive in a context characterized by Schumpeterian competition, simply producing a given set of goods, or employing a given set of inputs and process technologies, is not enough. To be successful over a long period of time, firms must develop the ability to innovate and then to profit from that innovation (Nelson, 1991). Different endowments of innovation capabilities - i.e., different stocks of technological knowledge and different degrees of efficiency 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 argued that there is a stable association between the stock of innovative capabilities owned by the firm, its output and its economic outcomes. However, whilst the stock of knowledge and the underlying learning process through which it is accumulated are unobservable, the appearance of product and process innovations can be regarded as a signal that valuable learning has occurred. Hence, they can be expected to account for performance differences across firms (Geroski and Mazzucato, 2002).

From an empirical standpoint, there is a great deal of evidence supporting the idea that estimates of the relationship between innovation and performance is sensitive (among other factors) to the way that corporate performance and innovation are measured (Loof and Heshmatt, 2006). The former is usually based on market share, accounting profits, market value, sales growth, number of employees, and productivity growth. The latter is proxied either by traditional indicators, such as R&D expenditures and patent counts, or by the application of direct measures of innovation outputs, such as product announcements in specialist trade journals or share of new products in the firm's total revenue.

If one is comfortable with believing that companies behave as profit maximizing agents, then accounting profitability becomes a natural summary statistic of corporate performance. Unfortunately, this indicator displays unusual patterns of variation when compared with other measures of economic performance and also tends to understate performance differences among firms. Rates of growth of sales, employment and productivity,[2] on the other hand, exhibit similar behaviour and appear to be more reliable indicators for evaluation of inter-firm differences (Geroski, 1998).

The measurement of innovation activities is also problematic. Traditional indicators, such as R&D expenditures and patent counts, although extensively used in the literature, suffer from drawbacks that make their application questionable, in several contexts (Kleinknecht, 1993). The 'object' approach to innovation measurement (Archibugi and Pianta, 1996) or, more precisely, a literature-based innovation output indicator, has become a valuable alternative for coping with such drawbacks. The metric, broadly applied in previous empirical analyses (Coombs *et al*., 1996; Santarelli and Piergiovanni, 1996; Tether, 1998; Flor and Oltra, 2004), is a suitable indicator of innovative performance when measuring corporate results in terms of the degree to which companies actually introduce inventions into the market (Hagedoorn and Cloodt, 2003). It also offers remarkable advantages over extant indicators (Kleinknecht *et al*., 2002): it provides a direct measure of how many new products or services are introduced to the market; 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, degree of complexity or other criteria; 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).

Empirical research on company growth and innovation activity points to some regularities across industries and over time. On the one hand, corporate growth rates appear almost random and can be reasonably approximated by Gibrat's Law (Geroski, 1998), 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). However, there are some exceptions; there are several studies that suggest that there is a mean reversion process at work in some contexts, with initial size and age exercising a transitory effect on growth dynamics (Hall, 1987; Hart and Oulton, 1996; Goddard *et al*., 2002). Similarly, recent studies that draw upon the tradition of stochastic growth models (Ijiri and Simon, 1977) suggest that the observed distribution of growth rates departs from the expected Gaussian shape implied by Gibrat's Law, and instead 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 found (Del Monte and Papagni, 2003). Furthermore, works adopting an 'object' approach to innovation indicators (Table 1) suggest that although the tendency is for a positive link between innovation output and level measures of economic performance, no significant effect of successful innovation on sales growth rates has been identified generally.

[[Please insert Table 1 about here]]

Among several major contributions, Geroski *et al*. (1997) analyse a panel of 271 stock market quoted UK firms for which data on major innovations and granted patents were available. They find that neither of these sets of variables (in current and lagged values) has any impact on firm growth, and that excluding them from the model does not affect the 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 is measured, Geroski and Mazzucato (2002) show that this is not so. These authors examined the link between product and process innovations introduced by US car manufacturers and their growth rates over a long period, from 1910 to 1998. Despite the evidence that lagged output is correlated with corporate growth to some extent, no significant effect of different measures of innovation is evident. Bottazzi *et al*. (2001) provide further evidence on this point. Using detailed information for the world's large pharmaceutical companies over an 11 year period, they find that the introduction of neither new chemical entities nor patented products affects firms' growth performance.

This piece of evidence[3] raises the crucial question of why no positive relationship between innovation and firm growth has been found, from an empirical standpoint. One reason might be that the degree of novelty of the innovation, its nature (product vs process), and the economic environment faced by the company, has a notable influence on the effect of technological developments on growth. Degree of product novelty may exercise two opposite effects on corporate revenue streams. On the one hand, an inertia effect might cause slower market acceptance of products with higher degrees of novelty. On the other hand, an efficiency effect might ensure more rapid acceptance of innovations that satisfy a compelling market demand. The magnitude of the two effects is likely to depend on the technological opportunities characterizing a given industry. Indeed, some studies show that the inertia effect prevails when few technological opportunities exist, whereas the efficiency effect is overwhelming when technological opportunities thrive (Barlet *et al*., 1998). In industries subject to rapid technological change, minor process innovations may be more effective than incremental product innovations. For example, the cumulative effect of incremental improvements in manufacturing technology led Japanese semiconductor producers to catch up with US pioneers during the 1980s (Rosenberg and Steinmueller, 1988).

Another reason is based on the empirical findings that, typically, all factors except size have a fairly small impact on firm growth. The argument here is that size may indirectly affect sales dynamics by conditioning the effects of other factors on it (Geroski, 1998). Thus, firms are aware that growth from innovation will be limited by their size (Cohen and Klepper, 1996). A third hypothesis originates in the observation that innovations are usually imitated within the space of one to three years, regardless of their value and whether or not they have been patented. This implies that the rents due to innovation are quickly dissipated (Levin *et al*., 1987). Accordingly, it is commonly assumed that firms benefit from their innovations through increased price-cost margins rather than higher growth (Cohen and Klepper, 1996).

The above discussion addresses those factors commonly alleged to influence the sign and magnitude of the link between innovation activity and corporate growth. In our study we investigate a different research hypothesis, which is related to the level of observation at which empirical analysis is typically conducted. We specifically conjecture that empirical investigation at different levels of analysis significantly changes the estimates of the impact of product innovation on sales growth rates. This reasoning hinges on the presumption in evolutionary economics that the loci of learning, innovation, competition and changes in market share, are to be found at a much more disaggregated level than the standard four digit industries (Dosi *et al.*, 1995), i.e. at the level of submarkets. It is among clusters of firms producing homogeneous products, that draw upon a similar knowledge base, use a common production technology and target the same customer group, that processes of technological innovation and imitation are expected to emerge as major drivers of firm growth.

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 biggest problem is that those variables are counts of innovations whose technological and/or economic value may differ substantially and therefore, they cannot be simply added, one by one, to generate a concise indicator. If this heterogeneity is not taken into account, then the values of innovativeness assigned to each company will not be directly comparable because they have been computed by algebraic summations of somewhat different objects (Tether, 1998).

Our investigation is confined to the IC industry (5-digit SIC code 36741), a high-technology context comprising relatively stable market segments. We start with a 'corporate' level analysis on the assumption presuming that IC are a homogeneous product and that their commercialization is the only business activity in which the sample firms are involved. We consider a semiconductor taxonomy that allows us to identify 18 distinct submarkets,[4] each of which contains relatively homogeneous groups of products with peculiar functional technologies, average selling prices, ultimate applications and sales dynamics. Building upon the resulting industry breakdown, we define an individual 'business unit' as a firm's activity within a given market segment (Cohen and Klepper, 1996; Gimeno and Woo, 1999). Consequently, in our sample, semiconductor producers may be a single business unit or, several business units competing in distinct market 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 need to check for the other factors mentioned above. The limiting role of current size, and the costs associated with plant expansion, do not seem to be a major concern in our setting for two reasons. First, both integrated device manufacturers (firms that realize internally, the production of the components they sell) and fabless companies (firms that outsource the majority of their finished wafer supply to 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 expenditure that occurred in the early 1990s, the industry has been experimenting with a long wave of overcapacity that shields companies with no internal facilities from the risks of not having access to production services (IC Insights, 2004).

Limiting the focus to a single industry helps neutralize the confounding effect that patent protection may exercise on the innovation-growth relationship. This effect is a major concern for intersectoral studies involving firms characterized by varying degrees of propensity to patent. Furthermore, studies that deal with appropriability conditions emphasize that patents, although important, do not secure semiconductor companies from the risk of imitation by competitors and the consequent dissipation of innovation rents (Levin *et al*., 1987).

In our study, we deal only with product innovations. Thus, it could be argued that the estimated relationship between innovation and corporate growth rate will depend on the degree of novelty of the new devices. Unfortunately, the only information we have on new products is year of introduction and branding company, which prevents us from distinguishing, for example, among components that are new to the firm but not to the market, and those that are new to both. However, interviews with industry operators clarified that the type of products we are considering are incremental innovations (discussed further in the next section). In taking account of these characteristics of our innovation data, and bearing in mind that the efficiency effect prevails in industries subject to rapid technological change (Barlet et al., 1998), we would expect to find a non-significant association between incremental product innovations and corporate growth rates. Notwithstanding this, we expect that shifting the analysis from the corporate to the business unit level will change the significance and magnitude of the estimated relationship.

2 Descriptive Analysis

2.1 The Data Set

The statistical analysis performed in this paper exploits a unique and original data set covering a sample of IC producers from around the world. The uniqueness of our data set stems from the ability to disaggregate the information on sales and product innovations into reasonably homogeneous clusters. These are the so-called submarkets 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 on a taxonomy commonly used by research companies to identify homogeneous groups of semiconductor products. The taxonomy is built around three major characteristics of IC: 1) their functional technology - IC components can be divided into analogue and digital devices; 2) their degree of customization - ICs are classified as standard devices and custom devices; 3) the final applications for which custom devices are tailored - communication infrastructures, computers, storage devices, consumer electronics, automotive and industrial systems. The resulting industry breakdown comprises 18 clusters which roughly correspond to segments at the 7-digit SIC level.[5]

The data set was compiled by merging information on sales figures from the Competitive Landscaping Tool (2005) and the Strategic Reviews Database (2001, 2004),[6] with data on product announcements gathered from trade, engineering and technical journals accessible from numerous sources.[7] Since we are interested in the role of product innovation on incumbents' growth, we selected a balanced panel of IC producers that were continuously active in the period 1998-2004. The matching procedure resulted in a sample of 95 companies[8] accounting for about 80% of total revenues from IC and representative of the population of IC producers.[9]

2.2 Size Distribution

IC revenues represent total semiconductor shipments for some 70% of companies in our sample. For 90% of these producers, they account for more than 70% of semiconductor revenues, while for almost 8% of companies IC revenues represent less than 50% of their semiconductor production. If $S_i(t)$ is the IC sales of firm i $(i \in [1,\ldots,95])$ at time t $(t \in [1998,\ldots,2004])$, we can define the overall size[10] of each producer as $s_i(t) = \log(S_i(t))$. Values reported in the top group in 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 $s_i(t)$ throughout the period of analysis.

[[Please insert Table 2 about here]]

The average size of the industry sharply increased in year 2000, when it topped its maximum historical value of US$177 bn In 2001, a 33% downturn brought the industry back to its 1999 values. Since then, the evolution of company size has followed a smoother pattern of expansion. The computed values for 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. Nevertheless, it seems plausible to assume that a log normal is a first, reasonable approximation of the size distribution of IC producers.

2.3 Growth

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

Applying analysis of variance, we can categorize total variation in growth rates across firms and over time, into two components, ‘between’ and ‘within’ variation. The former reflects differences in firms which persist over a period, thus identifying permanent differences between firms. The latter reflects variations in the growth of a typical firm over time, thus suggesting that transitory differences can affect firm performance over time. Computed values show that 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-to-year differences in the growth rates of IC producers persists for more than one period.

2.4 Product Innovation

Our product innovation data include a unique collection of new semiconductor devices commercialized during the period 1998-2004 by producers from around the world. Interviews with industry operators clarified that the type of items likely to warrant 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.[11] We know the part number (the company reference code that uniquely identifies a given product) associated with each component, the name of the company that commercialized it and the year and month in which the product was announced. Also, we have included a brief description that allows us to assign each component to one of the 18 submarkets in our taxonomy.

The descriptive statistics (bottom group 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 in the years thereafter. Also during 1998-2002, the deviation around the mean increased whereas the coefficient of variation was stable around 1.1. Computed values for skewness suggest that the distribution of product announcements is right skewed, meaning that most firms introduce only a 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 ranges from a minimum of 5 in 1998 to a maximum of 9 in 2003. Computed values for the first and third quartiles show that 25% of companies released a maximum of 4 new product announcements, while 75% of them recorded about 17 announcements during the seven years.

The classification of IC by market segments allows us to deepen our investigation. None of the firms in our sample introduced new components in all 18 submarkets, while 18 firms (19%) announced new products in one segment only. Among the sample firms, 52.6% introduced new devices in a maximum of three segments and 89.5% innovated in less than ten, providing support for the idea that IC 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 top ten IC vendors in 2004. Pairwise correlation coefficients of 0.6 and 0.7 respectively, suggest that there is a positive link between average firm size and number of new product announcements, and between average firm size and number of submarkets in which it operates.

3 Econometric Analysis

The econometric analysis is conducted in two stages. We start by investigating the impact of firm innovativeness on global growth performance, assuming IC to be a homogeneous product and looking at the IC business as a whole. Then we divide the sales figures and product announcements of each company, by its constituent business units and explore the innovation-growth relationship at a finer level of observation. In both stages, we first test Gibrat's Law in order to assess whether current size should be factored into the model describing the evolution of growth rates. Then, we augment the baseline model in order to verify whether incremental product innovations enhance the growth performance of IC producers (Del Monte and Papagni, 2003; Oliveira and Fortunato, 2006).

3.1 Innovation and Corporate Growth Performance

We begin our exploration from a classic benchmark in the empirical literature: the relationship between firm size and firm growth (Sutton, 1997). This stream of research compares the null hypothesis that growth rates are random, and hence that Gibrat's Law applies, with the alternative that mean reversion induces a convergence in firm sizes, in the long run. Empirical studies typically concentrate on the following model:

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

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 growth rate.

Application of this model raises two issues. First, if heterogeneities in the steady state sizes or in the speed of convergence of firms are neglected (i.e. assuming $\alpha_i = \alpha, \forall i$, and $\beta_i = \beta, \forall i$) then estimates of the degree of convergence may be biased (Geroski *et al*., 2003). The availability of panel data sets mitigates this type of problem by properly accounting for heterogeneity across firms. Second, the disturbance term in Eq. (1) might be serially correlated because of the persistence of chance factors that cause the firm to grow abnormally quickly or abnormally slowly. The presence of serial correlation induces dependence between the lagged dependent variable $s_{i,t-1}$ and $\varepsilon_{i,t}$ thus generating inconsistent estimates of β in typical panel data with large N and small T (Chesher, 1979).

Departures from Gibrat's Law occur when the null hypothesis $H_0 : \beta_i = 1$ is rejected in favour of the alternative[12] $H_1 : \beta_i < 1$. The latter implies the existence of mean reversion, or that small firms in period *t* will grow faster than larger ones in *t+1*. In this case, if $\alpha_i > 0$, firms will converge to different steady sizes, equal to $-\alpha_i / \beta_i$, even within the same industry.[13] A concern when using microeconomic panel data sets is that some estimators of autoregressive models, such as Eq. (1), do not identify the parameter of interest when the time series is not stationary. Since the early 1990s, unit root tests have been recommended to cope with this problem, with the aim of providing inferences on stationarity and cointegration by combining information from the time series and the cross-sectional dimensions (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 the equation (1) with the stochastic process generating $s_{i,t}$ modelled as:

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

The above specification reveals that there is no fixed effect under the null hypothesis, 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 than 1. 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). Using data for IC 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 the 1% significance level. To summarize: our empirical investigation shows that Gibrat's Law does not hold in our sample.[14] Accordingly, we need to include current size as an explanatory variable in the model describing the growth rate of the firm.

Given the foregoing evidence, we further augment the baseline specification of our model by including a one-year lag of the dependent variable together with a set of regressors capturing the influence of product innovation over rates of growth. We specify the following regression equation:

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

where $\Delta s_{i,t}$ is the rate of growth of the IC 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 θ(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 $v_{i,t}$ are assumed to be identically and independently distributed.

[[Please insert Table 3 about here]]

Table 3 presents the estimated coefficients associated with the explanatory variables included in the econometric model. We report OLS (Ordinary Least Squares) and Differenced GMM (General Method of Moment) estimates for comparison only. We do not comment on them because of the finite sample biases they suffer from in short panels with persistent time series and individual fixed effects (Bond, 2002). We focus instead on the System GMM estimates (Arellano and Bower, 1995; Blundell and Bond, 1998) reported in columns 3 and 4 of Table 2. 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 $\Delta v_{i,t}$, but not significant second order serial correlation) is consistent with the assumption that the $v_{i,t}$ disturbances in Eq. (3) are serially uncorrelated. Furthermore, the Hansen test for instrument validity suggests that the model is correctly specified and the computed coefficients are consistent.

When we look at the estimated parameters, we can see that the coefficient associated with lagged size is negative (above -0.15) and statistically significant at the standard 5% level. This implies that a mean reversion process indicates that small companies grow faster than larger ones. Conversely, growth experienced in the previous period has a positive and statistically significant effect on current growth performance. Estimated coefficients show that only product announcements dated *t-2* have a positive and significant effect (0.5%) on the growth performance of the firm. Although relatively short, the lag structure specified for the variable measuring innovativeness covers a period in the life cycle of a typical semiconductor device that lasts until the decline stage (ICE, 1999). In addition, a *differenced Hansen* test supports the idea that the regressor $I_{i,t}$ can be treated as a predetermined variable.[15] This result is consistent with previous research which found that firm growth had no impact on contemporaneous innovation rates in high-technology industries (Audretsch, 1995; Klomp and Van Leeuwen, 2001).

We comment briefly on the magnitude of the estimated innovation coefficients and the finding that only past product announcements seem to positively affect firm growth. However, before doing so, we need to ascertain whether and how the foregoing evidence changes when we shift to the business unit level.

3.2 Innovation and Growth at Business Unit Level

The database for this investigation is indexed by firm, submarket and year. Specifically, index *i* identifies companies $(i \in [1,\ldots,95])$, the index *j* identifies market segments $(j \in [1,\ldots,18])$, and the index *t* identifies time[16] $(t \in [2001,\ldots,2004])$. The pair of subscripts *ij* identifies an individual business unit belonging to firm *i-th* and operating in segment *j-th*. With a complete panel, we would have 1,710 observations. In practice, not all firm-submarket combinations are available because firms do not compete in every submarket. We define active business units as those that record positive sales in the Competitive Landscaping Tool database. Also, we retain in our sample only units that were continuously active during the period 2001-2004. After this cleaning procedure, we are left with a working sample of 372 units observed over four years.

We start by investigating whether growth rates behave according to Gibrat's Law of proportionate effects. To this end, we model the size evolution of a business unit through the following stochastic process:

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

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 small number of periods available, several procedures devised to test for the presence of a unit root cannot be immediately applied in our framework. To cope with this problem we apply a simple t-test[17] proposed by Bond et al. (2005) and based on the OLS estimator of β in Eq. (4):

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

Under the null, $\beta = 1$, t_{OLS} has an asymptotic standard normal distribution as $N \rightarrow \infty$ for fixed T. OLS estimates for Eq. (4) when correcting for autocorrelation and within group heteroskedasticity, return a parameter β equal to 0.992. Using this estimated coefficient we compute a t_{OLS} statistic of -0.9, a value within the acceptance region of the null hypothesis, suggesting that past size does not affect current growth when working with disaggregated data (Growiec *et al.*, 2008). Here, we take a step forward and model the relationship between growth and product innovation as follows:

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

The specification in Eq. (5) differs from the corporate level one, since the variable capturing the effect of past size is excluded. Also, we drop the dynamic specification[18] and include in the estimated equation only the variables for product innovation and the parameters controlling for firm and time specific effects. There are two reasons why we do not include a variable for unobserved effects at the business unit level. First, the specification in Eq. (4) implies that this type of heterogeneity depends on parameter β and disappears when this parameter is equal to 1, which is the case here. Second, groups of components which we treat as distinct market segments may actually be organized under a single division in a given firm. This implies that unobserved, time-invariant individual effects may be expected to exist at firm level rather than being associated with individual business units. This assumption has two important consequences: i) we can work with data in levels, a non-trivial benefit given the short panel available; ii) we can enter further lags of the innovation variable thus capturing persistent effects of sustained incremental innovation over time.

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

To account for the existence of time-invariant effects at corporate and submarket levels, we augment the model with firm and submarkets dummies. This means that we come close to, but are 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, submarket effects are not.[19] Although the introduction of firm dummies significantly improves the explanatory power of the model, causing the R^2 to increase to 0.16, there is still a large fraction of unexplained variation in the dependent variable. In the model with firm dummies only, the size of the coefficient for contemporaneous product announcements shrinks, and its significance drops to below the conventional level. Conversely, the contribution to growth performance of devices commercialized in the most recent past remains stable.

[[Please insert Table 4 about here]]

To summarize, the econometric analysis carried out in this section shows that marginal increments do matter. Product announcements in the most recent past have a positive effect on growth rates at both corporate and business unit levels. Despite the statistical significance of the estimated coefficients, we need to know whether their magnitude is to some extent negligible and why only past innovations have an impact on the growth performance of sample firms.

With respect to the first point, it should be noted that only two of the studies reviewed above, estimate a positive relationship between innovation and growth. Mansfield (1962) computed an average effect of major innovations on a firm’s growth rate, in the range 4% to 13%. Loof and Heshmatt (2006) found that only innovations that are new to the market have a positive effect on the rate of firm growth, equal to 7.1%. Bearing these results in mind, and considering that we deal only with incremental innovations and do not make a distinction based on degree of novelty, an average 0.5% effect of innovation on firm growth rate does not seem irrelevant. Furthermore, in accordance with our research hypothesis, the estimated coefficients are higher when we shift from the corporate to the business unit level of analysis.

We also think that the significant impact of new products announced at time *t-2* is not surprising. Indeed, product announcements typically refer to products in the sampling stage which usually precedes the production stage by approximately three months. Jointly considering these characteristics of our innovation data and the observation that the revenues from a generic semiconductor product usually peak during the second year after commercialization (ICE, 1999), makes our results less ambiguous than they initially appeared.

4 Conclusions

While there is a large body of the theoretical literature that indicates that innovation is a powerful factor underlying firm success, the empirical research provides conflicting evidence. Several studies (Geroski *et al*., 1997; Bottazzi *et al*., 2001; Geroski and Mazzucato, 2002) that use sales growth rates as a measure of firm performance and adopt an ‘object’ approach to innovation indicators, do not find a significant association between successful innovations and corporate growth rates. There is hard empirical evidence suggesting that the estimated relationship between innovation and firm performance is sensitive to such factors as data sources, estimation methods, and the way that corporate performance and innovation activity are measured (Loof and Heshmatt, 2006).

The research hypothesis in this paper is that, since firms embody rather idiosyncratic bundles of products, the level of observation (4-digit SIC level) at which empirical analysis is typically conducted is not appropriate to track the processes of learning, innovation and competition (Dosi *et al*., 1995). It follows that empirical investigations conducted at different levels of analysis would yield significantly different estimates of the innovation-growth relationship. Shifting to a fine-grained level of analysis allows us to account for technological and economic differences in the value of counted innovations, which literature-based innovation indicators tend to overlook (Tether, 1998). Neglecting this type of heterogeneity might bias the computed rate of innovativeness in such a way that a fairly accurate inference can be drawn from inter-firm comparisons.

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 IC industry. Employing a standard taxonomy of semiconductor components, we arranged the data in 18 clusters of relatively homogeneous products, a feature that distinguishes our contribution from previous research in the field. Our econometric analysis aimed at measuring the impact of product innovation on the global growth performance of IC producers and the growth performance of their constituent business units.

At corporate level, the incremental innovations introduced in the most recent past seem to significantly affect (0.5%) the growth performance of IC producers. This result supports the idea that incremental innovations affect the firm's ability to sustain its market position (Rosenberg and Steinmueller, 1988) by leveraging the capabilities to innovate accumulated 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). At the same time, a process of mean reversion drives the evolution of global corporate size, while positive effects associated with past growth performance persist, at least in the short term.

The econometric analysis performed at business unit level supports the hypothesis in this study that the influence of incremental product innovations on focal unit growth is higher than that recorded at corporate level. IC components commercialized in the most recent past account for an almost 1% increase in sales, although they explain only a small portion of growth rate variation.

The empirical investigation in this paper can be extended in two directions. Firstly, we could assess whether products characterized by higher degrees of novelty have a greater impact on growth rates than more minor innovations. Secondly, we could examine how the introduction of new components by competitors, in each submarket, affects the performance of the focal firm, and whether there are positive spillovers from innovations in adjacent submarkets.

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Table 1 Empirical studies of the effect 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 Inn.	Positive						
Robinson, 1990	238 start-ups	US	Product Inn.			Positive				
Kleinschmidt & Cooper, 1991	125 industrial firms	Canada	Product Inn.			Positive				Positive
Geroski *et al*., 1993	721 quoted firms	UK	Major Inn.							Positive
Banbury & Mitchel, 1995	Implantable cardiac pacemakers industry	US	Product Inn.			Positive			Positive	
Cesaratto & Stirati, 1996	Manufacturing firms	Italy	Inn. Propensity	Unrelated	Unrelated		Unrelated	Positive		
Geroski *et al*., 1997	271 quoted firms	UK	Major Inn.	Unrelated						
Roper, 1997	Small firms	UK-D-IR	Inn. Propensity					Positive		
Crepon *et al*., 1998	Manufacturing firms	France	Inn. Propensity				Positive			
Tether & Massini, 1998	Small firms	UK	Inn. Propensity		Positive					
Blundell *et al*., 1999	340 manufacturing firms	UK	Major Inn.							Positive
Roberts, 1999	Pharmaceutical firms	US	Inn. Propensity							Positive
Bottazzi *et al*., 2001	Pharmaceutical firms	World	Product Inn.	Unrelated						
Llorca Vivero, 2002	Manufacturing firms	Spain	Process Inn.				Positive			
Geroski & Mazzucato, 2002	Automobile producers	US	Prod/proc Inn.	Unrelated						
Loof & Heshmati, 2006	Manufacturing firms	Sweden	Inn. Propensity	Positive[a]						
Cainelli *et al*., 2006	735 service firms	Italy	Inn. Propensity	Unrelated			Positive			

(*a*) Loof and Heshmatt (2006) find a positive and significant impact of innovations new to the market on sales growth of manufacturing firms but no effect for innovations new only to the firm. They find no effect for either type of innovation on sales growth in the service sector.

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

Table 3 Determinants of growth at 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 x 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
Diff-Hansen test				0.127

1. Values in parenthesis are Student's *t*-test. Standard errors are asymptotically robust to heteroskedasticity.
2. m1 and m2 are tests for first-order and second-order serial correlation, asymptotically N(0,1). They test the level residuals for first-differenced residuals from GMM estimates.
3. GMM DIFF results are one-step estimates. GMM SYS estimates are the two-step version requiring Windmeijer finite-sample correction.
4. Hansen is a test for overidentifying restrictions for the GMM estimators, asymptotically χ^2. *P-value* is reported.
5. Diff-Hansen tests the validity of the extra moment conditions available when $Innovation_{i,t}$ is treated as a predetermined (GMM SYS 2) rather than an endogenous variable (GMM SYS 1). *P-value* is reported.

Table 4 Determinants of growth at business unit level

Dependent variable: $Growth_{ij,t}$			
	Model 1	Model 2	Model 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)
$Innovation_{i,t-3}$	-0.003	0.0002	-0.0002
	(-0.54)	(0.03)	(-0.04)
$Innovation_{i,t-4}$	-0.006	-0.0004	0.0008
	(-1.54)	(-0.09)	(0.19)
Firm dummies		Sig.	Sig.
Submarket dummies			Not Sig.
Time dummies	Sig.	Sig.	Sig.
Constant	-0.05	-0.06	-0.17
	(-1.95)	(-1.39)	(0.90)
Observations: N x 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. Values in parenthesis are Student's *t*-test. Standard errors are asymptotically robust to heteroskedasticity.
2. The 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.

[1] In line with the extant literature (Chesbrough, 2003) we treat the terms submarkets and market segments as synonymous in this paper.

[2] Studies on employment growth rates investigate differences in the propensity of companies in different size classes, to create jobs (Hart and Oulton, 1996). Studies of sales growth rates take account of how product market risks affect the successful introduction of innovative components in the marketplace (Barlet et al., 1998).

[3] Recent contributions provide similar findings for the services sector. Cainelli *et al*. (2006) do not find any significant association between a set of innovation variables (e.g. service innovation, product innovation, ICT expenditure per employee, R&D, etc.) and the growth rates of Italian services companies. Loof and Heshmatt (2006) obtained similar results for a panel of Swedish firms.

[4] See Appendix A in Corsino (2008) for a detailed description of submarkets resulting from the breakdown of the IC industry in this paper.

[5] According to the Gale Thompson PROMT database the Static Random Access Memory segment in our taxonomy is associated with product code 3674125, digital signal processors with product code 3674129, and microprocessors with product code 3674124.

[6] The Competitive Landscaping Tool, published by iSuppli, Inc., is a market share database enabling users to extract data on leading companies, disaggregated by market segment, for the period 2001-2004. The Strategic Reviews Database, released by IC Insights, Inc., is a complete database of financial, strategy, product, and technology information on more than 200 of the world's leading IC manufacturers and fabless suppliers.

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

[8] Most of the companies not covered in our sample are located in Taiwan and China. New product announcements for these firms were not available from the trade and specialist journals. The other firms not included are those mainly involved in the production of Application Specific IC - components designed and manufactured for the exclusive use of one customer - and a few diversified companies, for which internal transfers represent a significant fraction of their total IC revenues (e.g. IBM Microelectronics, Sony and Sharp).

[9] We compared the first four moments of the size distribution of the companies in our sample with those of two larger samples of firms from the Competitive Landscaping Tool: (i) an unbalanced panel of 193-205 companies; (ii) a balanced panel of 174 firms for the period 2001-2004.

[10] We choose sales turnover as a measure of business size rather than an 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, since 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 activity in IC business.

[11] Products for which IC producers do not generally issue a press release are: (i) existing products in a new package; (ii) existing products with incremental changes to their features.

[12] The case $H_1 : \beta_i > 1$ is typically excluded because it would imply diverging firm sizes, meaning that large firms would grow faster than smaller ones and would grow increasingly larger.

[13] Even if the null hypothesis is not rejected, Gibrat's Law may fail because: (i) the error term in equation (1) is autoregressive, $\varepsilon_{i,t} = \rho\varepsilon_{i,t-1} + \nu_{i,t}$, so that above-average growth in a period tends to extend into the following year (ρ > 0), or tends to be followed by a period of below-average growth (ρ < 0); (ii) the standard deviation of growth rates varies with firm size, that is, when the fitted residuals in Eq. (1) exhibit heteroskedasticity, $\sigma_\varepsilon^2 = \sigma_\varepsilon^2(i,t)$.

[14] We obtained the same results when we performed the test over a subset of 85 companies with sales figures available for 9 continuous years.

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

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

[17] Bond et al. (2005) argue in favour of this test, stressing that consistent tests of the unit root hypothesis require consistent estimation only under the null hypothesis. 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 $\varepsilon_{ij,t}$.

[18] 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 null of no serial correlation in the error term of Eq. (5).

[19] In Model 2, the F test on the group of firm dummies gives a value of 3.57. In Model 3, the F tests on the groups of firm and submarket dummies give values of 2.88 and 1.57 respectively.