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This article addresses an issue that is debated in the economics of innovation literature, namely the existence of increasing returns to R&D expenditures and firm size, in product innovation. It explores further how the firm's structural characteristics and contextual factors affect the sustained introduction of new components over a relatively long time period. Taking advantage of an original and unique database comprising information on new product announcements by leading semiconductor producers, we show that: (i) decreasing returns to size and R&D expenditures characterize the innovation production function of the sampled firms; (ii) producers operating a larger product portfolio exhibit a higher propensity to introduce new products than their specialized competitors; (iii) aging has positive bearings on the firm's ability to innovate.

**Keywords:** R&D; firm size; product innovation; semiconductor industry

*JEL Classification*: L11; L63; O31; O32

## 1. Introduction

This article addresses some empirical issues related to the innovative performance of business organizations operating in a high-technology context, the semiconductor industry. It assesses specifically the existence of increasing returns to expenditures on research and development (R&D) and firm size in the production of new components. Moreover, it explores how the variables relating to the general characteristics of the firm (age, vertical integration, diversification) as well as contextual factors (geographic localization, abundance of technological opportunities) affect the dynamics of product innovation.

Since their invention, semiconductor devices have been applied in an increasing number of markets ranging from computers to telecommunications, consumer electronics, automobiles, aerospace and military equipment, home appliances and industrial systems (Tilton 1971; Dosi 1984; Langlois and Steinmueller 1999). This was accompanied by transformations in the organization of economic activities along the semiconductor value chain (Macher, Mowery, and Hodges 1998; West 2002; Tokumaru 2006) and the management of product standards and intellectual capital (Gruber 2000; Stuart 2000; Hall and Ziedonis

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2001) and the emergence of regional clusters of semiconductor companies (Saxenian 1994; Kim 1998). All these factors are illustrative of the peculiar context of the semiconductor industry for empirically oriented research in the fields of industrial organization, strategic management and organizational behavior.

Despite the extensive semiconductor economics literature, little attention has been paid to the forces driving the introduction of incremental product innovations by incumbent firms and how differences in the innovative behavior of competing organizations evolve over time. There are two possible reasons for the limited interest paid to these issues. On the one hand, there is a tendency to overlook the role of incremental innovations in discussions of technical change. On the other hand, there is a shortage of appropriate data on the output side of the innovation process, a somewhat important drawback affecting the whole of the literature dealing with technological change. These shortcomings in the literature, and the desire to foster our knowledge of what drives incremental innovations, are the key motivations for the present study.

The first goal of this article is to provide original evidence on the innovative performance of a representative sample of firms operating in a setting where the introduction of new products, on a cost-effective and timely basis, affects a firm's ability to sustain its competitive position. Exploiting unique data on product announcements by leading semiconductor producers, we aim at verifying how the structural and strategic characteristics of the firm influence its rate of innovation. Furthermore, in having monthly innovation data we are able to implement non-parametric methods for the analysis of recurrent events, which allows us to investigate the cumulativeness of the innovation activity.

The article is organized as follows. In Section 2, we review the literature concerning the determinants of firms' innovative performance. In Section 3, we provide some descriptive statistics of the innovation data and other characteristics of the sampled companies. Moreover we discuss evidence from the application of non-parametric methods to recurrent events. Section 4 presents the results of the econometric analysis. In Section 5, we provide a few concluding remarks.

## 2. Determinants of innovation performance

Schumpeter's writings, in the first half of the twentieth century, saw the role of innovation as a key driver of economic growth and inspired a large body of studies exploring the determinants and economic consequences of technical change. Schumpeter (1950) himself and the economic theorizing that was built on his work supported the idea that large corporations enjoy a relative advantage in the supply of innovation, over small business organizations.[1] Size emerges as a primary internal force driving technological innovation (Cohen and Levin 1989; Cohen 1995; Becheikh, Landry, and Amara 2006) and its relevance stems from several intertwined arguments.[2]

One set of justifications refers to size *per se*. It is often claimed that large firms can exploit economies of scale in the financial market to secure the finance for undertaking risky R&D projects, more cheaply than small firms (Fisher and Temin 1973). Under capital market imperfections, large corporations may also be expected to have an advantage in securing finance for risky projects because size is associated with rapidly accessible and stable flows of internally generated funds (Cohen and Levin 1989). Along with financial resources, large size is a prerequisite for attracting the technical and managerial expertise required to undertake a profitable innovation process. Only firms large enough to command these resources will achieve the temporary monopoly power associated with innovation and be able to pursue further technological advance in order to grasp future profits

(Kamien and Schwartz 1975). Also, large organizations may be more able to reap the rewards of innovation because of their better ability to ease the penetration of new products, through their widespread marketing and distribution facilities. Furthermore, they can establish strategic alliances and supply relations, encourage innovative behavior by the partners involved and eventually benefit from their achievements (Rothwell and Dodgson 1994).

Another set of justifications relates to the R&D technology and its complementarities with other business functions. The conjecture here is that there are economies of scale in the R&D function itself that only large corporations can take advantage of. This is a two-part argument. On the one hand, a large R&D staff can be more efficient than a small one (Fisher and Temin 1973). On the other hand, an R&D staff of a given size may be more productive in a large firm 'as a result of complementarities between R&D and other non-manufacturing activities' (Cohen 1995, 184).

The literature has also discussed factors that convey a relative advantage to small firms undertaking innovative activities. Rothwell and Dodgson (1994) argue that small business organizations enjoy *behavioral* as opposed to the *material* advantages accruing to larger competitors. Specifically, bureaucratic structures may hinder the undertaking of new projects due to the resistances that spread across organizational layers, while the entrepreneurial management of small firms may benefit from rapid decision-making to grab technological and market opportunities. In addition, the lean and focussed organization of small firms, in placing innovation activity at the center of its competitive strategy, safeguards and endorses the creative impulses of technical personnel, which the conservatism of hierarchical structures might thwart (Acs and Audretsch 1990).

Empirically oriented works in this tradition typically interpret the findings, among R&D performers, that R&D rises proportionately with firm size, as indicating that size offers no advantage in the production and commercialization of innovation (Cohen 1995). However, deriving such a conclusion from the empirical evidence concerning the association between firm size and innovative effort may be meaningless, unless additional assumptions are taken into account. Indeed, Fisher and Temin (1973) and Kohn and Scott (1982) show that, to the extent that Schumpeter's hypothesis can be given a clear formulation, it must refer to a relationship between innovative output and firm size, not to a relationship between R&D spending and firm size. This observation has stimulated scholars investigating the Schumpeterian conjecture to look for appropriate measures of any output of the innovation process.[3]

Patent counts and patent citations are a first, useful option. Their use as indicators of technological activities hinges primarily on the recognition of the importance of technical change in the competitiveness and growth of firms. Beyond that, improvements in the technologies of information storage and retrieval allow systematic access to the information contained in patent documents (Griliches 1990). These advantages notwithstanding, patent statistics suffer from shortcomings that advise caution when they are used to assess the innovative performance of organizations (Archibugi and Pianta 1996; Kleinknecht, Van Montfort, and Brouwer 2002). The raw count of patents and patent citations can be considered a measure of inventive performance rather than innovative success (Freeman and Soete 1997); however, even where patents are treated as an intermediate output of R&D activities, puzzles and anomalies emerge (Hall, Griliches, and Hausman 1986; Patel and Pavitt 1995).

In recent years, remarkable efforts have been made to propose alternatives that cope satisfactorily with the drawbacks affecting traditional indicators. New indicators have appeared that include shares of imitative and innovative products in firms' total sales, the collection of major innovations by means of interviews with technical experts (Pavitt, Robson and Townsend 1987) and the count of new product and process announcements in trade, engineering and technical journals (Kleinknecht, Van Montfort, and Brouwer 2002). This last, known as a literature-based innovation output indicator (Coombs, Narandren, and Richards 1996; Flor and Oltra 2004), is considered an ‘object’ approach to innovation measurement[4] since it concentrates on the innovations themselves. It represents an adequate indicator of innovative performance in terms of companies’ results on the degrees to which they actually introduce inventions into the market (Hagedoorn and Cloodt 2003). In addition, it offers remarkable advantages over extant alternatives: it is a direct measure of the market introduction of new products and services; the data are relatively cheap to collect, and are publicly available, reducing the need for firm questionnaires; it is possible to split the data by type of innovation, market niche, degree of complexity; 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, 161).

An outstanding example of the use of this indicator is the US Small Business Administration’s Innovation Data Base, which includes 8074 innovations commercially introduced in the USA in 1982 (Edwards and Gordon 1984). Using these data for a sample of more than 200 industries, Acs and Audretsch (1988) found that the number of innovations commercialized had increased less than proportionately than R&D expenditures. Later studies using the same database, estimated a firm production function for innovation output and found that decreasing returns to firm size and R&D expenditures were the norm among US companies at the beginning of the 1980s (Acs and Audretsch 1990). Spurred by this research, a series of contributions published during the 1990s explored the innovativeness of large and small firms in other countries (Coombs, Narandren, and Richards 1996; Santarelli and Piergiovanni 1996; Wakasugi and Koyata 1997; Kleinknecht, Van Montfort, and Brouwer 2002). This stream of empirical work supports the idea that small and medium-sized companies account for a share of total innovations that is far larger proportionately than their share of employees and record a higher number of innovations per unit of R&D expenditure (Tether 1998). In addition, although a positive correlation between R&D expenditures (or alternatively firm size) and innovation output has been found (Becheikh, Landry and Amara 2006), the evidence supporting the idea that there are increasing returns to product development is scant.

There are some limitations, however, that prevent us from considering the conclusions from previous research as unambiguous. Most published work analyzes only a single cross section of data, thus neglecting how firm size affects innovativeness over time (Stock, Greis, and Fischer 2002). Also, the interpretation of the empirical evidence so far collected depends on the assumption of equivalent technological (and economic) significance of the innovations introduced. While normally unstated, this assumption may be misleading and the conclusions related to innovativeness and firm size could change when it is properly taken into account (Tether 1998).

The present study draws on the literature-based, innovation output method to investigate the Schumpeterian hypothesis, using firm-level data from the semiconductor industry. Our baseline analysis explores how firm size and R&D investments affect the commercialization of incremental product innovations by established semiconductor producers. Although sometimes underemphasized in discussions of technical change, incremental innovations account for long periods of time in terms of the stages through which technology evolves (Tushman and Anderson 1986), and can significantly affect a firm’s ability to sustain its market position (Rosenberg and Steinmueller 1988). Since incremental innovations elaborate and extend a particular, dominant design, while reinforcing the capabilities of established organizations, they can be particularly valuable for firms operating in mature industries (Henderson and Clark 1990). Qualitative evidence from companies' reports corroborates this argument and supports the idea that introducing new products, on a cost-effective and timely basis, is a major concern for companies operating in the semiconductor industry.

We extend our baseline specification to include other general, strategic and contextual determinants of firms' innovativeness. We take account of how aging encroaches on organizational innovation, an issue not adequately addressed in the otherwise extensive literature[5] dealing with the organizational factors supporting technological change (Becheikh, Landry and Amara 2006). On empirical grounds, the net effect of age on innovation hinges on two opposite forces. On the one hand, the stock of knowledge and organizational competences positively affect a firm's ability to pursue technological advances and improve its innovation rate. In many technologies, its current achievements depend strongly on previous efforts and learning, which, as time goes by, develop into the capabilities to innovate and to profit from innovation (Nelson 1991). On the other hand, if aging leads to rigidities in communication flows within the boundaries of the firm, and rivalry in the face of technical advances in the surrounding environment, innovation will decrease as firms get older (Sorensen and Stuart 2000).

The strategic choice to pursue a higher degree of vertical and horizontal specialization rather than integrating along the value chain and/or offering a diversified product portfolio may influence the firm's innovative output. Once again, the balancing of opposing forces (e.g. the nature and complexity of the innovation under scrutiny, the need for complementary assets, the appropriability regime and the technological opportunities characterizing the competitive environment) will determine the net impact that a firm's boundaries have over its innovative rate. Vertically specialized producers may achieve higher innovative scores than their integrated counterparts because of their alleged dominance in isolating and solving problems. Likewise, horizontally specialized firms may outperform diversified competitors deploying an array of competing units to tackle a specific problem (Robertson and Langlois 1995). Conversely, diversified producers may have more opportunities to exploit the unpredictable results of research activities (Nelson 1959) and the complementarities that arise from a broader and more coherent portfolio of activities in which a single innovation is closely tied to the set of succeeding ones (Nelson 1991).

## 3. Data, variables and descriptive statistics

### *3.1. Sample*

The working sample employed in this study comprises 95 international companies operating in the worldwide semiconductor and related devices industry (SIC CODE 3674). These companies account for more than 80% of total revenues from the semiconductor industry and are representative of the population of semiconductor producers. The procedure used to select these firms was based on two main criteria: (1) we consider only firms that operated continuously in the semiconductor industry during the period 1997–2004; (2) among these, we selected only those companies for which complete data about product introductions and financial statements were available for at least 5 continuous years during the observation period. This screening procedure implies that only listed companies were retained in our sample, with privately owned firms and operating divisions of large conglomerates (primarily Japanese producers) excluded from the analysis.

Detailed information on the product innovation activity of surveyed companies was retrieved from product announcements released by semiconductor companies, which appear on technical journals only after positive assessment by technical experts. Interviews with industry operators clarified that products covered by press releases in trade, engineering and technical journals are: (i) new product families; (ii) new members of an existing productfamily, incorporating new features; (iii) new products with substantial enhancement to existing features.[6] Accordingly, we can assume that the innovations included in our analysis coincide with technologically improved products as defined in the Oslo Manual (OECD 1997). The availability of such data distinguishes our analysis from previous research insofar as it allows the exploration of those factors driving the subsequent introduction of incremental innovations in a high-tech industry.



### 3.2. *Dependent variable*

Following an 'object' approach to innovation indicators (Smith 2005), we use product announcements as a proxy for firms' innovative performance. Data on product announcements for the companies surveyed were gathered from various trade, engineering and technical journals accessed via the Gale Thompsons PROMT database, the Markets and Industry News database, the OneSource database and press releases available on companies' web sites. We examined a huge number of product releases in order to select announcements describing product introductions (excluding events such as product enhancements, product information, product developments, etc.) and deleted duplicates in the collation of these announcements. We ultimately obtained a unique collection of some 8470 releases concerning semiconductor devices commercialized during the period 1998–2004.

The semiconductor firms in our sample, on average, accounted for slightly more than one product announcement per month (Table 1). This level was fairly stable along the entire period, with the exception of a peak in 2002 just after the downturn that affected the entire electronics industry. The specificity of this year emerges further if we consider that the maximum number of product announcements per month in 2002 was 19, a higher value than was observed for other years. When data on product announcements are aggregated on a yearly basis, we get an average number of releases ranging from 9.2 in 1998 to 14.8 in 2002. The corresponding median takes a minimum value of 5 and a maximum of 9 in years 1998 and 2003, respectively, while the coefficient of variation ranges from 1.09 to 1.24. The low values computed for the median suggest that the distribution of product announcements is right skewed, meaning that most firms introduce a small number of components, while a very few producers account for a large fraction of the innovation output observed.

### 3.3. *Independent variables*

The innovative effort of sample firms is measured by the (logarithm of) annual *R&D* expenditures[7] (Table 2), deflated in 1998 US dollars. When employment (i.e. the proxy

Table 1. Descriptive statistics for product announcements observed on a monthly base.

| | Mean | Std dev. | Median | Min | Max | Std dev./mean |
|---|---|---|---|---|---|---|
| 1998 | 0.74 | 1.22 | 0 | 0 | 10 | 1.61 |
| 1999 | 0.99 | 1.51 | 0 | 0 | 10 | 1.54 |
| 2000 | 1.04 | 1.57 | 0 | 0 | 10 | 1.52 |
| 2001 | 1.12 | 1.69 | 1 | 0 | 12 | 1.52 |
| 2002 | 1.24 | 1.94 | 1 | 0 | 19 | 1.59 |
| 2003 | 1.18 | 1.75 | 1 | 0 | 12 | 1.49 |
| 2004 | 1.09 | 1.69 | 1 | 0 | 11 | 1.55 |

Table 2. Sample statistics.

| | Mean | Standard deviation | First quartile | Median | Third quartile | Min | Max |
|---|---|---|---|---|---|---|---|
| Product announcements[a] | 13.33 | 15.4 | 3 | 7 | 17 | 0 | 112 |
| Employment (thousdands of employees)[b,c] | 1.16 | 1.82 | 263 | 778 | 3283 | 22 | 88,447 |
| R&D ($M 1998)[b,c] | 10.69 | 1.62 | 16.00 | 39.48 | 141.33 | 0.93 | 4365 |
| Age in 2004 | 24 | 13 | 16 | 20 | 30 | 7 | 57 |
| Diversification | 0.31 | 0.42 | 0 | 0 | 0.64 | 0 | 1.51 |
| Technological opportunity | 5.76 | 1.28 | 5.62 | 6.12 | 6.44 | 0 | 6.57 |
| *D* (fabless firm) ($N = 283$) | 0.50 | | | | | | |
| *D* (US firm) ($N = 490$) | 0.87 | | | | | | |

[a]564 observations (95 firms) 1999–2004.
[b]564 observations (95 firms) 1998–2003.
[c]For this variable, the geometric mean and the standard deviation of the logarithm are shown.



of firm size) is also included in the regression model, we normalize the variable measuring R&D spending by the total number of employees to avert confounding the R&D impact with the size effect (Crepon, Duguet, and Mairesse 1998; Hall and Ziedonis 2001). In this way, any spare effect related with the normalized R&D variable would single out the existence of differential abilities in searching for new opportunities among firms.

Firm *size* is proxied by the (logarithm of) total number of employees at year ends. It is worth noting that employment data refer to the whole labour force of the firm, because information disaggregated by organizational functions are not available. The impossibility of clearing the employment variable of its R&D component may induce a double-counting problem which, eventually, leads to a downward bias in the coefficient associated with the (normalized) R&D variable (Hall, Mairesse, and Mohnen 2009).

Firm's *age* (gauged by the logarithm of the difference between the current year and the year in which the firm was founded) is included in the model to assess whether competencies and experience firms accumulate along time positively affect their ability to sustain a sequencing of product introductions.

The organization of economic activities along the value chain is important for differentiating companies in the semiconductor industry. Spurred by the adoption of the complementary metal-oxide semiconductor (CMOS) process at the beginning of the 1980s (Macher, Mowery, and Hodges 1998), the industry went through a process of vertical disintegration that led to the emergence of two types of firms commercializing physical components. There are the integrated device manufacturers (IDMs), which are companies that internally realize the design, production and marketing of the components they sell. And there are fabless companies, which outsource the manufacturing services to external suppliers while maintaining the design and marketing of products in house. If we group the sampled companies by this structural feature we obtain two clusters comprising 47 IDMs and 48 fabless firms. Accordingly we define the dummy variable *fabless* which equals 1 if the company does not manufacture in-house the components it commercializes.

In contrast to the bulk of previous research, which looked at the semiconductor industry as a homogeneous setting, we take account of the high degree of within-industry heterogeneity by considering firms' horizontal boundaries. We adopt an industry breakdown that distinguishes six product markets and allows us to cluster companies according to the number of markets in which they operate. The industry breakdown is based on a taxonomy commonly used by industry practitioners to identify homogeneous groups of semiconductor products (World Semiconductor Trade Statistics 2008). The six product markets are: (1) discrete components; (2) optoelectronics and sensors; (3) standard and commodities; (4) microcomponents; (5) memories; (6) application-specific devices. Drawing upon this industry breakdown and exploiting information on sales figures of each company by product market we measure firm diversification (Jacquemin and Berry 1979) by a time-variant variable, *diversification*, defined as:

$$\sum_{i=1}^{6} p_i \log\left(\frac{1}{p_i}\right)$$

where $p_i$is the share of the $i$th product market's sales in the total revenues of the firm.

Firms can operate different product portfolios within an industry and diverse product markets in the same industry can offer dissimilar degrees of opportunity to innovate. Therefore, some firms may focus their operations in product markets with a relatively higher pace of technological advances. To account for these firm-specific differences, we adopt an indicator that captures the magnitude of technological opportunities companies face (Ahuja 2000). First, we identified for each firm the product markets in which it was active in each year. Second, we considered the total number of new product announcements in that set of product markets. Thereafter, taking the firm's own distribution of product announcements across the selected markets as weights, we computed a weighted measure that gages the comparative richness of the firm's specific environment. Relatively high values of this variable (i.e. *technological opportunity*) signal that the range of product markets the firm addresses offer more opportunity to introduce incremental improvements than other markets.

Finally, notice that the majority of firms in our sample (82) are public companies headquartered in the USA, six are located in Europe and the remaining seven are East Asian producers. To control for the geographic localization of the firm we define the dummy variable *US firm* which equals 1 if the firm is headquartered in the USA.

### 3.4. Patterns of product sequencing

To shed some light on how the vertical and horizontal boundaries of the firm shape the sequencing of product innovations, we trace and compare the patterns of product announcements for distinct groups of firms along the entire period of analysis, using monthly data. To carry out this exercise, we adopt an approach (Nelson 1988, 1995; Lawless and Nadeau 1995) that focusses on cumulative mean functions (CMFs) to analyze the processes of recurrent events without full probabilistic specification of the processes. In our case, we define the CMF of the number of product announcements $N_i(t)$ occurring over the interval $[0; t_i]$ for each firm $i (i \in [1, \dots, K])$ as $M(t) = E[N_i(t)]$. A non-parametric and robust estimator, $\hat{M}(t)$, of this function is given by:

$$\hat{M}(t) = \sum_{s=0}^{t} \hat{m}(s) = \sum_{s=0}^{t} \frac{n(s)}{\delta(s)}, \tag{1}$$

where $\hat{M}(t)$ is the mean number of product announcements observed at time $t$, calculated by dividing the total number of announcements, $n(s)$, released by all firms, $\delta(s)$, still under observation at time $s$. The variance estimator used to construct the confidence interval for the mean function is:

$$\hat{V}(t) = \sum_{i=0}^{K} \left[ \sum_{s=0}^{t} \frac{\delta_i(s)}{\delta(s)} (n_i(s) - \hat{m}(s)) \right]^2, \quad (2)$$

where $\delta_i(s)$ is equal to 1 if the $i$th firm is still under observation at time $s$and 0 otherwise.

Figure 1 shows $\hat{M}(t)$ for the product announcements of IDMs versus fabless companies (Figure 1(a)) and diversified firms versus single business producers (Figure 1(b)), with associated 95% confidence intervals. It appears that, along the entire period, vertically integrated firms are more likely to release product announcements than their specialized rivals. It is also clear that companies operating a wider product portfolio are more likely to innovate than firms competing in a single product market.

A plot of the natural logarithm of $\hat{M}(t)$ against time (Figure 2) shows that the differences in the estimated CMF values for IDMs and fabless companies are approximately constant. This implies that discrepancies in the propensity to innovate of the two organizational profiles tend to be stable over time.

Fabless companies typically compete in just one of the six product markets in our industry breakdown, the ASD market (Corsino and Passarelli 2009). Accordingly, the innovative performances of fabless companies and IDMs should be evaluated within this specific market rather than considering the whole semiconductor industry. To do this, we selected companies operating in the ASD market and retained only their product announcements of new components in that market. The resulting sample comprises 85 companies (42 IDMs and 43 fabless) accounting for about 4370 product announcements. A plot of $\hat{M}(t)$ against time (Figure 3) shows that even at this level of analysis vertically integrated manufacturers outperform their specialized competitors. Although the curves representing the estimated CMFs of the two groups are closer than was observed before, their confidence intervals do not overlap. This suggests that differences in the innovative scores of the two groups remain statistically significant.

## 4. Econometric analysis

### *4.1. Statistical method*

The Poisson distribution represents the most commonly used stochastic model to deal with events, like product innovation, whose occurrences are non-negative integer values. Its density function takes the form:

$$\Pr[Y = y] = \frac{e^{-\lambda}\lambda^y}{y!}, \quad y = 0, 1, 2, \ldots, I, \quad (3)$$

while the first two moments are, respectively, $E[Y] = \lambda$ and $V[Y] = \lambda$, hence the equidispersion property of the model. The Poisson regression model is derived from the above distribution by parameterizing the relationship between the expected number of occurrences $\lambda$ and covariates $x$ (Cameron and Trivedi 1998).

Following the standard hypothesis of an exponential mean parametrization, we assume that the expected number of product announcements for the $i$th firm ($I_i$) is an exponential function of some firm characteristics $x_i$:

$$E[I_i|x_i] = \lambda_i = \exp(x_i'\beta). \quad (4)$$

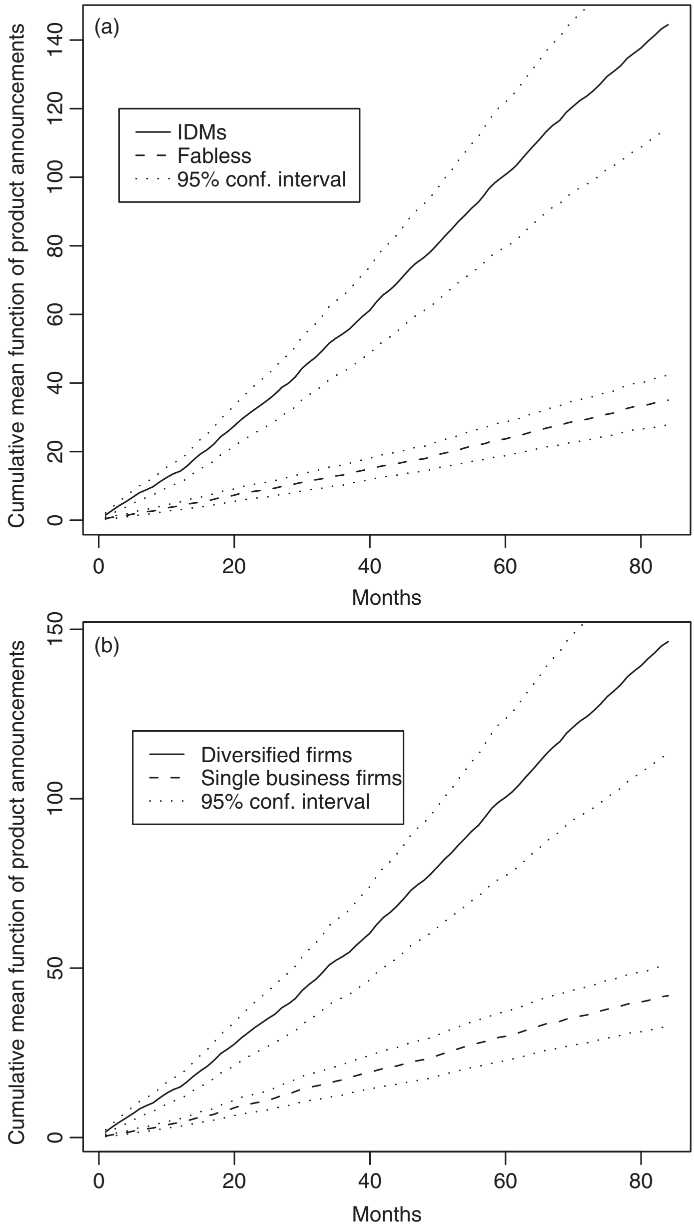


Figure 1. Estimated CMFs: (a) IDMs versus fabless firms; (b) diversified versus single business firms.

An appealing feature of this model is that consistency of estimated parameters does not require the data to be Poisson-distributed, but just the weaker assumption of correct specification of the conditional mean. This notwithstanding, the Poisson regression model is often too restrictive in many applications. Two common characteristics of data used in applied research prevent valid statistical inference to be drawn from the Poisson model. On the one hand, the Poisson distribution predicts a share of zero counts that is considerably

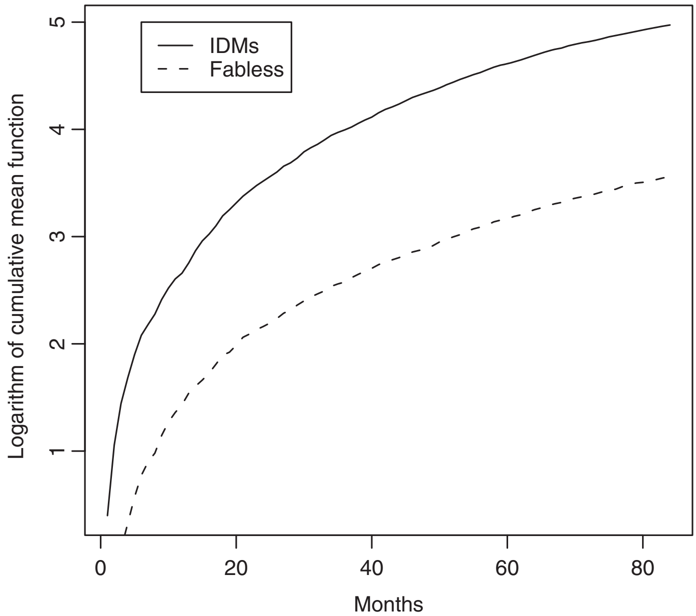


Figure 2. Logarithm of estimated CMFs.

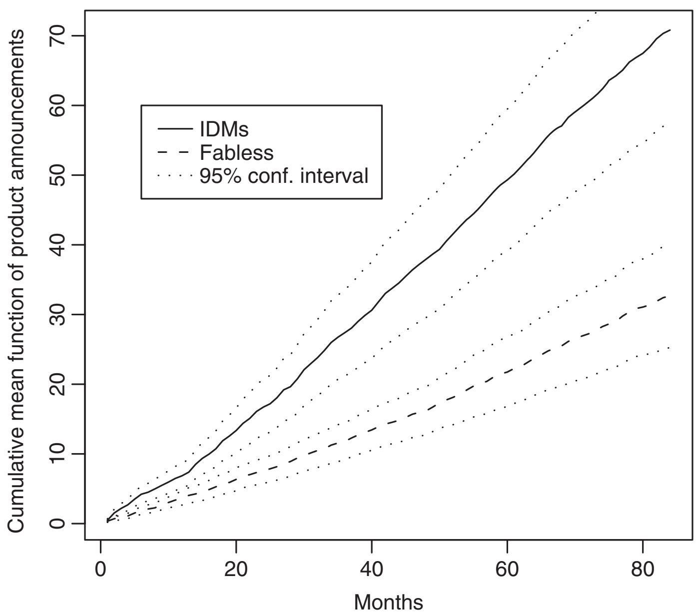


Figure 3. Estimated CMFs in the ASD market.

lower than what observed in many samples[8] (zero excess problem); on the other hand, the equality of mean and variance is typically violated in the data (overdispersion problem).

The Poisson *pseudo*-maximum-likelihood estimator is a first option to deal with the violation of the equidispersion property. It maintains the conditional mean assumption used in the Poisson model but relaxes the equidispersion hypothesis by adopting a robust variance–covariance matrix of the sandwich form. A second approach to cope with the overdispersion problem is the negative binomial (NB) model which explicitly accounts for overdispersion in the conditional mean assumption. The NB model can be interpreted as a continuous mixture model arising out of introducing unobserved heterogeneity in the specification of the conditional mean, i.e.

$$E[I_i|x_i, \varepsilon_i] = h_i\lambda_i = \exp(x_i'\beta + \varepsilon_i), \tag{5}$$

where $h_i = \exp(\varepsilon_i)$ is assumed to have a gamma density function, $g(h|\alpha)$, with mean 1 and variance $\alpha$. In the most common variant of the NB model, known as the NB2 model (Cameron and Trivedi 1998), the expected number of product announcements for each firm corresponds to the first moment of the NB distribution, $E[I|\lambda, \alpha] = \lambda$, while the variance function exceeds the mean and is equal to $V[I|\lambda, \alpha] = \lambda(1 + \alpha\lambda)$.

Although the NB model generally provides a better fit to the data than the Poisson model, other possibilities exist to opportunely improve on the Poisson estimator. When repeated cross-sections on a sample of individuals are available, as it is the case in our empirical investigation, panel data techniques (Cameron and Trivedi 1998) become an appealing alternative to the pooled NB regression model. These methods look at the latent heterogeneity behind the overdispersion problem as a result of time-invariant individual characteristics, usually unobservable to the econometrician, which may induce correlation in the outcomes observed in successive periods. For the Poisson panel data model, the expected number of product announcements for the $i$th firm at time $t$ ($I_{it}$) can be written as:

$$\begin{aligned} E[I_{it}|x_{it}, \alpha_i] &= \alpha_i\lambda_{it} \\ &= \alpha_i \exp(x_{it}'\beta + \gamma_t) \\ &= \exp(\delta_i + x_{it}'\beta + \gamma_t), \end{aligned} \tag{6}$$

where $\delta_i = \ln(\alpha_i)$ and $\gamma_t$ is a time specific mean. It is worth reminding that the $\alpha$ used here refers to the individual effects rather than being an overdispersion parameter as it was in the NB model. Moreover, Equation (6) suggests that although the individual effects in the conditional mean are multiplicative, rather than additive as in the linear model, they can still be interpreted as a shift in the intercept. Two alternatives can be distinguished: the fixed-effects model where the $\alpha_i$ are unknown parameters, and the random effects model where the $\alpha_i$ are instead iid random variables. Beyond that, Hausman, Hall and Griliches (1984) proposed the NB2 random effects model as an additional case which explicitly accounts for overdispersion and, unlike the Poisson specification, allows randomness both across firms and across time. In what follows, we will apply the modeling strategy sketched above to assess how the factors outlined in our review of the literature influence the innovative performance of sampled companies.

### *4.2. Results*

Table 3 shows the estimated coefficients for the pooled NB specification. Before commenting on these results, two considerations are worth making. First, diagnostic statistics reported at the bottom of the table reveal that a Poisson specification[9] would not provide a good fit to our data insofar as it discards the heterogeneity characterizing observations in our sample. In fact, the overdispersion test returns a value of about 0.36 for all regression models thus signaling that the assumption of equality between mean and variance underpinning

Table 3. Pooled NB estimates, 1999–2004 (564 observations).

| | Model (1) | Model (2) | Model (3) | Model (4) |
|---|---|---|---|---|
| Firm R&D$^{a}_{t-1}$ | 0.265*** | 0.225*** | −0.042 | −0.153 |
| | (0.041) | (0.039) | (0.081) | (0.106) |
| Firm size$_{t-1}$ | | | 0.332*** | 0.313*** |
| | | | (0.046) | (0.051) |
| Firm age$_{t-1}$ | 0.155 | 0.296** | −0.019 | −0.007 |
| | (0.125) | (0.107) | (0.138) | (0.131) |
| Fabless$_{t-1}$ | −0.942*** | | −0.642*** | |
| | (0.178) | | (0.164) | |
| Diversification$_{t-1}$ | | 0.956*** | | 0.675*** |
| | | (0.145) | | (0.168) |
| US firm$_{t-1}$ | 0.351 | 0.520** | 0.499** | 0.668*** |
| | (0.209) | (0.191) | (0.194) | (0.181) |
| Technological opportunity$_{t-1}$ | 0.124** | 0.135*** | 0.154*** | 0.173*** |
| | (0.040) | (0.035) | (0.040) | (0.036) |
| Year 2000 | −0.055 | −0.054 | −0.052 | −0.051 |
| | (0.055) | (0.060) | (0.055) | (0.062) |
| Year 2001 | −0.106 | −0.156* | −0.064 | −0.080 |
| | (0.069) | (0.075) | (0.068) | (0.075) |
| Year 2002 | −0.039 | −0.131 | 0.043 | 0.013 |
| | (0.076) | (0.083) | (0.082) | (0.096) |
| Year 2003 | −0.085 | −0.169 | 0.017 | −0.001 |
| | (0.086) | (0.095) | (0.092) | (0.108) |
| Year 2004 | −0.158 | −0.263** | −0.053 | −0.079 |
| | (0.082) | (0.092) | (0.092) | (0.110) |
| Constant | −1.521* | −2.390*** | 1.761 | 2.159 |
| | (0.593) | (0.515) | (1.067) | (1.328) |
| Overdispersion test | 0.387*** | 0.413*** | 0.359*** | 0.360*** |
| Log-likelihood | −1803.563 | −1820.357 | −1785.108 | −1786.524 |
| LR test | 2020.20*** | 2056.11*** | 1862.58*** | 1788.68*** |
| Number of parameters | 12 | 12 | 13 | 13 |

Notes: Dependent variable: number of product announcements of each firm at year end. Standard errors in parentheses are heteroskedastic-consistent and robust to within cluster correlation. The likelihood ratio test evaluates the NB model versus the Poisson specification. The method of estimation is maximum likelihood.
[a]Log R&D in columns one and two; log R&D per employee in columns 3 and 4.
*$p < 0.05$.
**$p < 0.01$.
***$p < 0.001$.

the Poisson model does not hold. Furthermore, the likelihood ratio test rejects the Poisson specification in favor of a model that directly accounts for the presence of unobserved heterogeneity.

Second, the variables *fabless* and *diversification*, which portray the vertical and horizontal boundaries of the firm, display a somewhat high negative correlation (−0.59). This suggests that fabless companies not only specialize along the vertical chain but also operate a narrower product portfolio than their vertically integrated competitors: for example, 36 fabless companies (75%) were active in only one product market in year 2003. Horizontally specialized companies, however, are not necessarily fabless firms: the two largest producers in the industry, Intel Corp. and Samsung Electronics, both vertically integrated along the value chain, generate more than 90% of revenues from a single product market. To avoid a potential collinearity problem, we do not use simultaneously the two variables in the estimated regression models. Besides, since firm's diversification displays a certain variability along time, we limit our comments to those specifications that include *diversification* as a covariate.

Our empirical investigation does not lend support to predictions outlined in the Schumpeterian tradition. The estimated parameters reject the hypothesis that the increasing returns associated with either R&D spending or size *per se* characterize the production of new components in the semiconductor industry. Both covariates are expressed on a logarithmic scale, thus allowing an elasticity interpretation of the estimated coefficients. Results from Model 2 points out that doubling the R&D spending only leads to a 22.5% change in the expected number of product announcements, whereas Model 4 suggests that doubling firm size triggers a 31.3% increase. Once we control for firm employment, no residual effect spreads out from the variable gauging R&D intensity. Nonetheless, the scale coefficient is about 10 percentage points higher, thus implying that apart from the size of their R&D staff and facilities, large firms benefit also from other organizational functions. In particular, to the extent that the variable *size* discriminates between IDMs and fabless companies (the first quartile for the former is equal to 936 employees while the third quartile for the latter amounts to 507 employees), one can reasonably argue that it also captures the positive bearings arising out of the internalization of contiguous activities along the value chain (Monteverde 1995).

Although the estimated coefficients for the R&D and size variables do not lend support to the Schumpeterian hypothesis, we have to account for the effect of firm's diversification on product innovation to thoroughly assess the relative advantages accruing to large firms. To do this, a preliminary adjustment of the estimated parameter for the variable *diversification* is required because it does not enter logarithmically the regression model (i.e. the coefficient has a semi-elasticity interpretation). Hence, we rescale the parameter by the sample mean of *diversification* so as to compute $\hat{\beta}_{\text{div}} * \bar{x}_{\text{div}}$, which is a measure of elasticity (Cameron and Trivedi 1998). After this adjustment, we obtain an elasticity of 0.292 under Model 2 and 0.206 under Model 4. Consequently, the sum of the scale and scope coefficients (i.e. $0.225 + 0.292$ under Model 2 and $0.313 + 0.206$ under Model 4) returns a total elasticity of 0.52 for both specifications of the regression model.

The impact of age is somewhat controversial. The specification in column two reveals a positive and significant effect of aging on the expected number of product innovations (0.296). When we add firm size, however, the coefficient falls and no significant bearing seems to derive from the competencies and experience that firms accumulate as time goes by. Finally note that our choice of controlling for the relative abundance of technological opportunities in the firm-specific environment finds supports in the data: the variable *technology opportunity* is positive and statistically significant across all specifications.

The analysis thus far conducted rests on the assumption that the technological significance of new products does not vary significantly with the size of the innovating firms (Tether 1998). If such an assumption does not hold, our results would underestimate the magnitude of the scale effect and, hence, the relative advantages of large firms in product innovation. We carry out two robustness checks to assess the validity of this conjecture. Drawing on earlier research (Monteverde 1995; Leiblein, Reuer, and Dalsace 2002; Macher 2006), we recognize that different product markets in the semiconductor industry exhibit different degrees of complexity in technological development. In particular, product markets we identify in this study can be clustered into two distinct groups. A first group comprises analog and memory devices, i.e. components whose development requires an effective coordination of the design and manufacturing stages and the availability of search capabilities suited to cope with ill-structured technological problems. We regard new products in this group as characterized by a high degree of complexity. A second group, mainly digital logic devices, involves products whose design can be effectively assisted by EDA software and whose production by CMOS technology has lessened the interdependences with the manufacturing stage. We regard new products in this group as characterized by a low degree of complexity.

Thereafter, we analyze the distribution of new products by complexity and by the size category of the innovating firms. The exercise reveals that the share of high complexity innovations (31.1%) over the total number of innovations released by large firms (those with a total number of employees above the sample median) is slightly higher than the share of high complexity innovations (26.2%) commercialized by small enterprises. Such a differential does not convincingly points to the existence of any strong relationship between technological complexity of new components and firm size.

As a further check, we separately regress the counts of innovations with varying degrees of complexity on the set of explanatory variables reported in Table 3. In doing this, we opportunely control for the large number of zeros in the count of high complexity innovations (about 60%) by estimating a zero-inflated NB model. The results of the multivariate analysis (available from the authors on request) are highly consistent with estimates in Table 3. In particular, the coefficient associated with the size variable is 0.338 for low complexity products and 0.293 for high complexity devices. Moreover, a higher level of firm diversification has significant and positive bearings (0.436) only on the introduction of products whose development does not poses ill-structured problems. Overall, the foregoing evidence suggests that the assumption of equal technological significance of product innovations between size classes holds in our setting.

Panel count data models provide an alternative approach to deal with the overdispersion problem by modeling the latent heterogeneity in the conditional mean as firm-specific effects. The likelihood ratio tests reported at the bottom of Table 4 compare the panel estimator with the pooled estimator and highlights that idiosyncratic heterogeneity may be a concern in our sample. For example, under the specification in column two we obtain a $\chi^2 = 1983.82$ with a $p$-value of 0.000.

A number of considerations lead us to prefer a random effect method. First, the random effect specification may be more appropriate because our sample comprises relatively many firms but each of them is followed for a short period; in these circumstances, a fixed-effect method can produce inconsistent estimates (Greene 2003). Second, the fixed-effect model would exclude time-constant covariates, such as the one capturing the choice of outsourcing manufacturing services, which may have major bearings on the propensity to innovate of semiconductor firms (Hall and Ziedonis 2001). Finally, a Hausman specification test ($\chi^2 = 14.61$ with a $p$-value of 0.1471) corroborates our choice of adopting a random effect specification for the regression model.

Estimated coefficients reported in Table 4 endorse the idea that firms do not experience increasing returns to R&D spending in the production of new components. The elasticity of product innovation with respect to R&D is 0.168 for the panel Poisson model and 0.208 for the NB specification. The slight decline in these coefficients, when compared with the cross-sectional dimension, is due to the fact that after controlling for firm-specific effects the remaining share of within-firm variability is small.

The scale effect, measured by total employment, is still positive and statistically significant: the elasticities in columns two and four of Table 4 are, respectively, 0.253 and 0.288. To appreciate the overall size effect, we look again at how firm's diversification impinges on the release of new products. Unless the specification in column 2, we estimate a positive and statistically significant coefficient for the variable *diversification* in all other regression equations. After rescaling the parameters by the sample mean of the variable *diversification* and summing the obtained values to the coefficients of R&D and/or *size*, we compute the following elasticities: 0.24 for model Poisson (1); 0.33 for model NB (1); 0.38 for model NB (2).

Table 4. Panel data estimates – random effects model, 1999–2004 (564 observations).

| | Poisson (1) | Poisson (2) | NB (1) | NB (2) |
|---|---|---|---|---|
| Firm R&D$^{a}_{t-1}$ | 0.168*** | 0.006 | 0.208*** | −0.008 |
| | (0.035) | (0.049) | (0.037) | (0.060) |
| Firm size$_{t-1}$ | | 0.253*** | | 0.288*** |
| | | (0.038) | | (0.040) |
| Firm age$_{t-1}$ | 0.514*** | 0.303** | 0.351** | 0.115 |
| | (0.111) | (0.114) | (0.110) | (0.118) |
| Diversification$_{t-1}$ | 0.246* | 0.157 | 0.407*** | 0.304* |
| | (0.096) | (0.097) | (0.121) | (0.119) |
| US firm$_{t-1}$ | 0.234 | 0.357 | 0.306 | 0.430* |
| | (0.205) | (0.192) | (0.187) | (0.178) |
| Technological opportunity$_{t-1}$ | 0.075** | 0.086** | 0.066* | 0.077* |
| | (0.028) | (0.028) | (0.031) | (0.031) |
| Year 2000 | −0.033 | −0.024 | −0.035 | −0.016 |
| | (0.043) | (0.043) | (0.060) | (0.060) |
| Year 2001 | −0.055 | −0.015 | −0.070 | 0.006 |
| | (0.045) | (0.045) | (0.061) | (0.063) |
| Year 2002 | −0.010 | 0.062 | −0.033 | 0.077 |
| | (0.045) | (0.048) | (0.061) | (0.065) |
| Year 2003 | −0.082 | 0.009 | −0.084 | 0.046 |
| | (0.048) | (0.052) | (0.064) | (0.069) |
| Year 2004 | −0.173*** | −0.079 | −0.168* | −0.040 |
| | (0.050) | (0.054) | (0.065) | (0.071) |
| Constant | −1.630*** | 0.494 | −1.474** | 1.316 |
| | (0.453) | (0.636) | (0.499) | (0.775) |
| Log-likelihood | −1699.310 | −1688.950 | −1639.784 | 1629.920 |
| LR test | 2298.20*** | 1983.82*** | 387.54*** | 367.99*** |
| Number of parameters | 12 | 13 | 13 | 14 |

Notes: Dependent variable: number of product announcements of each firm at year end. Standard errors in parentheses. The likelihood ratio test compares the panel estimator with the pooled estimator corresponding to each specification. Hausman specification test: $\chi^2 = 14.61$, $p = 0.1471$. The method of estimation is maximum likelihood.

[a]Log R&D in columns one and two; log R&D per employee in columns 3 and 4.

*$p < 0.05$.

**$p < 0.01$.

***$p < 0.001$.

Differently from what we have found using a pooled estimator, parameters in three specifications of Table 4 suggest that age significantly and positively influences product innovation: hence, the positive bearings arising out of accumulating capabilities to innovate seem to outweigh the shortcomings and rigidities that aging may induce.

In summary, large firms enjoy relative advantages in developing incremental product innovations. Nonetheless, decreasing returns to scale, associated with either R&D spending or size, characterize the production of new semiconductor components. We estimate an overall elasticity of 0.52 using the pooled NB model and somewhat lower values ranging from 0.24 to 0.38 when adopting a panel data estimator. Our estimates are lower than the findings in Hall and Ziedonis (2001), who calculate a total scale coefficient of 0.99 for a sample of 95 US semiconductor producers over the period 1979–1995, using a pooled Poisson estimator. They are, however, in line with the findings in Hall, Griliches and Hausman (1986), who estimate an elasticity of 0.66 for a larger sample of firms.

The elasticity of product introduction to R&D, about 0.2, suggests that there are decreasing returns to scale in the search process, thus corroborating the idea that large firms are less efficient at R&D than their smaller competitors (Cohen and Klepper 1996). Although somewhat lower than results in earlier studies that use patents as an indicator of technological innovation (Griliches 1990), our estimates are quite similar in the cross-sectional and time-series dimensions. A plausible explanation for this result may be that product innovation data display a share of within firm variability that is larger than what observed in patent data. In our sample the within standard deviation is about 41% of the overall standard deviation, a larger share than the 17.8% and 24.8% characterizing patent counts in Hall, Griliches, and Hausman (1986) and Hausman, Hall, and Griliches (1984).

Even if large firms do not seem to reap any special advantage from an extended R&D effort, they can still obtain a higher technological performance by operating a wider range of products. Indeed, our analysis reveals that scope economies play a non-trivial role in fostering incremental technological advances. After controlling for size and the degree of technological opportunities in the surrounding environment, diversified companies appear more likely to sustain a sequence of incremental innovations over time. This upshot also matches the strategic response hypothesis that is alleged to explain the patenting activity of large semiconductor companies (Hall and Ziedonis 2001). Diversified firms, in fact, incur large sunk costs in complex manufacturing facilities and have strong incentives to carry out more R&D projects which may, eventually, enable them to innovate frequently and to spread their cost over a greater output. Finally, holding constant the scale and scope of the firm, our results lend support to the idea that as organizations age they effectively leverage the accumulated knowledge to nurture their innovative capabilities (Sorensen and Stuart 2000).

## 5. Conclusions

Whereas a large number of articles have investigated the sources and economic consequences of technological innovation, weaknesses in how applied researchers commonly measure innovation prevent us from deriving unambiguous implications from the bulk of the evidence so far collected. Two particular limitations in the existing literature deserve attention. First, we need to properly frame the role of incremental innovations in the discussion of technical change. Although sometimes underemphasized, incremental innovations account for long periods of time in the stages through which technology evolves (Tushman and Anderson 1986). They reinforce the capabilities of established organizations (Henderson and Clark 1990) and affect the firm's ability to sustain its market position (Rosenberg and Steinmueller 1988). Second, we need to address shortcomings in the traditional innovation indicators and look for suitable alternatives. Overall, the often inappropriate measurement of incremental innovations and the lack of satisfactory evidence on factors driving their introduction point to a need to fill this gap.

This article has tackled these limitations using original data for a sample of international semiconductor companies. Following an object approach to innovation indicators (Smith 2005), we collected detailed information on incremental product innovations commercialized by incumbent firms in the period 1998–2004.

To exploit the detailed information on the timing of product announcements, we conducted a preliminary analysis that avoids strong parametric assumptions about the recurrent event process. The non-parametric approach we adopted (Nelson 1995; Lawless and Nadeau 1995) estimates CMFs of the number of product announcements for groups of firms and identifies diverse patterns of product innovation as a function of varying structural characteristics of the firm.

Thereafter, using a range of econometric methods we addressed the innovation-size relationship, a landmark in the innovation literature. In line with previous research (Crepon, Duguet, and Mairesse 1998; Hall and Ziedonis 2001), we estimated an innovation production function where the dependent variable is measured as the total number of product announcements by a firm in a given year. The relevant explanatory variables are R&D spending, firm size and a number of other covariates that capture how general and strategic characteristics of the firm influence the propensity to innovate.

Our empirical investigation suggests that after controlling for the degree of technological opportunities in the firm-specific environment, decreasing returns to scale with respect to either R&D spending and firm size characterize the production of semiconductor components. Moreover, producers operating a larger portfolio of activities have a higher propensity to release product announcements than their specialized competitors. Also, a positive effect of aging on the number of product announcements generally appears from our econometric exercise. We finally notice that the estimated elasticity of product announcements with respect to R&D spending and firm size does not change when the technological significance of commercialized products is taken into account.

We would add a few remarks on desirable extensions to this work. It would be interesting to repeat our analysis including in the working sample both new entrants and firms leaving the semiconductor industry. It is plausible that considering only incumbent firms induces a sample selection bias that affects the estimated relationship between R&D expenditures (or firm size) and product innovation. Besides, it would be desirable to build on the results obtained using an event-history approach, which might shed light on features of the innovative behavior of business organizations yet to be uncovered.

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## Notes

1. This is the dominant logic according to the Schumpeterian Mark II model of innovation, a scenario 'characterized by relevant barriers to entry for new innovators, the prevalence of large established firms in innovative activities and the dominance of a few firms which are continuously innovative through the accumulation over time of technological capabilities' (Malerba and Orsenigo 1996, 60).
2. We discuss those arguments supporting the Schumpeterian perspective that have been advanced in the economics literature. See Damanpour (1992) for a complementary discussion based on the organizational theory literature. Moreover, in line with Nelson and Winter's (1982) interpretation of Schumpeter's work and the scarce support from existing empirical evidence (Cohen 1995), we disregard the effect of *ex-ante* market structure on innovative behavior and concentrate on the relationship between firm size and innovation.
3. The availability of reliable data on the output side of the innovation process is also a major concern for policy-makers interested in the sources of innovativeness, the incentives to promote it, and the ultimate impact of technological change over social welfare.
4. The literature dealing with innovation indicators distinguishes between two basic types of approaches: (i) a 'subject' approach which focusses on the innovating agent and relies upon firm surveys to gather data on firm-level innovation activity; (ii) an 'object' approach which focusses on the objective output of the innovation process and identifies technological innovation through expert appraisal or new product announcements (Archibugi and Pianta 1996; Smith 2005).
5. Notwithstanding the limited attention thus far, the topic is important insofar as it is neatly associated with the theme of whether aging has positive or negative effects on organizational functioning, a prominent issue in organizational ecology studies (Sorensen and Stuart 2000).
6. Products for which semiconductor producers do not generally issue press releases, and technical journals do not feature are: (i) existing product in new packaging; (ii) existing products incorporating incremental changes in various features.

7. Data on R&D spending and employment are from Compustat and the Strategic Reviews databases.
8. When compared with earlier research (see Table 1 in Guo and Trivedi 2002), the excess zero problem is not a concern in our case. In fact, the percentage of 0 innovations in our sample is 3.4%.
9. Estimates for the pooled Poisson specification are available from the authors on request.



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