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The relationship between firm size and innovation activity: a double decision approach

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1. Introduction

The main concern of this paper is to answer and test one of the most traditional hypothesis aforementioned by Schumpeter (1942) which states that innovation activity increases more than proportionally with firm size. The study of this effect and its explanation has produced a considerable body of empirical research (Levin et al. (1985)). Several reasonings justify a positive relationship between size of the firm and innovation. In a context of imperfect capital markets, large firms are associated with the availability of internally-generated funds. Second, there also exist scale economies in the technology of innovations. Another claim considers that the fixed costs of R&D are more easily to control if the innovating firm has a large volume of sales. Finally, large firms are more productive since there are complementary activities with innovations.

However, there are also arguments that support the opposite sign in the correlation of innovation and firm size. The proposition is that large firms enjoy sometimes a monopoly power, which discourages the creation of some technological advance. In fact, this alternative view finds that small firms are responsible of a disproportionate share of innovative activity (Holmstrom, (1989)). This claim comes from the agency theory and sustains that large firms might innovate less.

In the empirical analysis there are many difficulties to find satisfactory measures of new knowledge and the value of an invention which supposes a problem when trying to test this correlation. In fact, the measure of technical change or innovations is approximated by a variety of variables, distinguishing between inputs and outputs of an innovation. One feature of this paper is the use of an alternative output of innovation: the number of product innovations. An advantage of this measure compared to the use of patents as the dependent variable is that it retrieves the innovation activity of a firm because not all technical research transform in patents (Griliches, (1990)).

The estimation process consists in testing the firm size impact over the probability to innovate in product and verifying whether the decision to innovate is different to that about the number of innovations carried out. First, we estimate separately a Probit and a negative binomial models for the standard specification of the technological change function. Second, we set up a simultaneous doble-hurdle model using a Probit for the decision to innovate and a negative binomial for the number of product innovations engaged by the firm. When doing this, we are assuming that the determinants of the decission to innovate (or their effects) are different from those of the decision of how much to innovate. If this is so, results provided by univariate models are inconsistent. When estimating the model, we do not assume first hurdle dominance in the explanation of inexistence of innovations, but we test this hypothesis.

The information employed corresponds to the Encuesta Sobre Estrategias Empresariales (ESEE) provided by the Spanish Industry and Energy Ministery for the period 1990-93. One feature of this survey is the availability of a vast information of technical change at a firm level (among other characteristics) which, in our opinion, constitutes a good instrument to fullfil tha main objectives of the study.

Results provide clear indication about the existence of a double decision process. Size seems to have different effects in the two hurdles. In fact, the very small firms are the more dynamic ones in the decision to innovate. In contrast, if we consider the number of innovations equation, companies in all size intervals innovate less than those between 51 and 100 employees. Since the simultaneous model nests the univariate one, a likelihood ratio test also rejects the restricted specification. This adds new empirical evidence to the Spanish literature although in the majority of analysis the technical variable employed is the R&D effort (Paricio (1993)).

The rest of the paper contains four sections. Section 2 describes the data. We specify the model and explain the econometric techniques in Section 3. The empirical results joint with some policy implications are reported in Section 4. Section 5 concludes.

2. Data and stylised facts

A simple look to the data can help to motivate the main purposes of our study. The data set corresponds to the ESEE conducted over the period 1990-93 and surveyed over approximately 2,000 firms. This is an umbalanced panel since some firms cease to provide information due to several reasons (mergers, changes to non-industrial activity or stop in production process. New companies enter the survey each year in an attempt to maintain representativeness. In particular, it constitutes a mixture data set where a random sample is drawn up for small companies (with less than 200 employees) while for large firms (greater than 200 employees) the sample is exhaustive[1].

To offer a brief description of this survey we will use two indicators: production activity and firm size. However, the use of the firm size variable should be previously clarified. We can obtain a good measure through several proxies: total sales, total assets, capital stock or total employment. This survey has chosen the number of employees at 31 of December to approximate size. A common problem of this variable is the uncontrol

[1] This last aggregation and the threshold is suitable for the tipical spanish structure (Segura et al. (1993).

over workers' movements, so the solution adopted has been to get the firm employment average adjusting by possible modifications in the labour force level along the year.[2]

Refered to the production activity, the ESEE contemplates firms aggregated to 3-digit level corresponding to the manufactured sector with different firm participation. This classification can be easyly aggregated to the NACE-CLIO corresponding to 18 industries. We observe different firm behaviour according to size and industries, so while small companies are more present in Methalic products, Electric accessories, Food and Beverages and Textile industries, large companies are more frequent in Office machines and Precision tools sectors. Table A.1 in the Appendix help us to describe a cross tabulation of our sample during the 1993 distinguishing innovating from non-innovating firms. Such descriptives allow us to assess that from the 23,8% of innovating ones, the most dynamic sector is Leather. But we also observe that the very small companies of this sector engage in more product innovation than the remaining firms.

A very crude description of our data reveals how firm size affects the process innovating decisions in two different ways. First, when the argument is whether or not to innovate (Table 1) two intervals appear as much dynamic: firms with less than 50 employees and those in the group between 200 and 500 workers. We conclude that firm innovation does not follow a monotonic increase with the size as regards this decision, except probably for the third interval.

Table 1 around here

[2] Concretely, firms answer whether the employment alterations are due to changes in the fixed workers category or in temporary workers. For this last category, a question about how long have they been hired is also included.

Second, considering the decision about the number of innovations engaged. Cross tabulation amongst the six size intervals and the number of product innovations (Table 2) leads to a different conclusion. We differentiate three groups of innovating firms defined over three intervals of the count of innovations distribution.

Table 2 around here

In the three intervals considered we observe that firms with more than 500 employees carry out a larger number of innovations in comparison with the rest of groups. However, it is worth noting that a large firms does not necessarily engage in a more innovating activity; in fact, firms with 51-100 workers have an important count when they are doing several technical advances. A deep description of these facts can be analyzed using the following figures.

Figures 1 and 2 around here

We observe different shapes depending on the decision. Figure 1 provides evidence that the abnormal behaviour corresponds to the fourth interval with a few numbers of product innovations whereas figure 2 presents the third interval as the more dynamic in the decision to innovate.

Another feature that we would like to chek is the positive correlation between market power (measured as market share) and technical research. There are two arguments to sustain it. The deep pockets idea claims that dominant firms or firms with high market power have more capability to finance the search for innovations (Schumpeter, 1946). The second and alternative view is due to Gilbert and Newbery (1982) and has implications for industrial policy. Their proposal consists in assuming that dominant firms tend to innovate more because the reduction in search costs leads to gains in share as a result of the improvement in efficiency that probably small business can not afford. However, evidence provides different results concerning this relationship. Our concern is to confirm whether large firms have more incentives to innovate once controlling by the main variables affecting R&D activity. We present in Table 3 a crude tabulation between share and innovation as a preliminary evidence.

Table 3 around here

In this table we observe that during the time span of our sample the group with an intermediate market share is also firms which conduct some amount of innovations. Once the innovation research is conducted, it seems that firms with a medium market share engage in greater innovations than firms with a higher market power. The high figure (7.84) in innovation activity corresponds to firms in where the share is not much important which contradicts the theoretical proposition. A possible explanation of these results have been pointed out by several authors (see for a survey Levin et al. 1985). They state the unnecessity of large firms to develop some technological activity if they already enjoy of a dominant position in the market. Therefore, in this paper we will try to verify this argument, that is not always firms with high share engage in a more technological changes.

This analysis only covers the direct relationship between size and technical change while other varibles could affect the decisison to innovate and are possibly hiding other size effects. A more accurate test concerning the existence of a double decision process is presented in the empirical section.

3. Specification and estimation process

3.1. A theoretical framework

This work is set within the dynamic models of innovation activity determination.[3] The basic problem of a firm is to maximise its value which depends on inputs (physical and non-physical capital stocks) and their prices. Our objectives lead to consider the introduction of some search activity (S_{it}) as a gain for a better knowledge stock and a form to increase the probability of future innovation.

The formal model consists in a maximization of firm's value explained by the current profits and the present value of expected future profits:[4]

$$V_{it} = B(G_{it}, K_{it}, S_{it}, M_{it}, W_{it}) + \alpha E_t V_{it+1} \qquad [1]$$

α is the discount factor and E_t is the expectation operator conditioned to the firm's information set at t. Benefits depen on tangible capital (K_{it}), knowledge capital (G_{it}), search of activity (S_{it}), firm monopoly power (M_{it}) and other inputs that by hypothesis are maximised out of the problem (W_{it}). Profits can be written as total revenue minus total cost:

$$V_{it} = R(G_{it}, K_{it}, M_{it}, W_{it}) - C(S_{it}) + \alpha E_t V_{it+1} \qquad [2]$$

Notice that the cost function is only affected by the search for innovations. It captures the idea of cost reduction in the sense that the more R&D effort, the more firm efficiency.

[3] See Reinganum (1989) for a complete survey.
[4] See Blundell et al. (1995).

In the following, we will assume that G_{it} is determined by the number of innovations produced in the firm plus the past period knowledge which it depreciates at a rate (δ) as a result of the imitation:

$$G_{it} = I_{it} + (1-\delta)G_{it-1} \qquad [3]$$

We also need to specify the innovation production function, that is the relationship between R&D inputs and outputs. Suppose that the expected number of innovations depends on past search activity with f_i strictly increasing.

$$E(I_{it}) = f_i(S_{it-1}) \qquad [4]$$

In this function the relative productivity of search is a function of the technological opportunity, τ, in the industry so the marginal productivity will be $\partial f_{it} / \partial S_{it} = a(\tau_{it})$.

The consideration of [1]-[4] gives the first order conditions for S_{it}

$$-\partial V_{it} / \partial S_{it} = \partial C_{it} / \partial S_{it} \qquad [5]$$

which leads to the following equation for search:

$$S_{it} = g\left(M_{it}, K_{it}, a(\tau_{it}), X_{it}\right) \qquad [6]$$

The substitution of [6] in the knowledge production function provides an innovation equation which depends on the lagged values of market power, tangible capital, technological opportunity and other shifters (X_{it}):

$$I_{it} = h\left(M_{it-1}, K_{it-1}, a(\tau_{it-1}), X_{it-1}\right) \qquad [7]$$

3.2. The empirical specification

The empirical treatment of [6] and [7] drives to the estimation of two innovation equations: one in which we assume that innovation is described by a binary dummy and other where we use the count or number of innovations done in a firm.

$$I_{it}^{*} = g\left(M_{it-1}, K_{it-1}, a(\tau_{it-1}), X_{it-1}, \eta_i, v_t, \varepsilon_{it}\right) \qquad [8]$$

where $I_{it}=1$ if $S_{it}^{*} > 0$, and $I_{it}=0$ otherwise, in the first equation and $I_{it}>0$ if $S_{it}^{*} > 0$, and $I_{it}=0$ otherwise, in the second equation.

Equation [8] explains the innovation activity through their main determinants. The market power recovers the availability of the firm to achieve a dominant position in the production market. We take the market share and the employmen level as measures of relative and absolute size of the firm, respectively. The tangible capital captures the positive effect of internal financing on research activity via reduction in costs. Technological opportunity, τ, reflects the influences of technological push in the industry which occurs when exogeneous changes in scientific and engineering knowledge reduce the costs of new processes and so, increase the benefit of the firm (Lunn, (1986)).

On the other hand, X_{it}, a variable which picks up all other shifters, can be amongst them a measure of market structure. Hence, a common used proxy could be the concentration ratio. The sign of this variable is ambiguous. While one expects that more concentration leads to a lower cost of innovation and a larger effort and production of technological activity, there also exists evidence in the opposite view: a more concentrated market leads to lower effort in research because dominant firms does already have a dominant position. We test those hypothesis in the empirical analysis.

Finally, η_i refers to firm specific effects, v_t to macroeconomic time shocks and ε_{it} to the standard error term.

In the following an explanation of how those variables are aproximated in this study is presented. The dependent variable is measured through two ways in order to distinghish the two decisions. First, whether the firm innovates or not in product is considered by a dummy variable (NIPOS). Second, the decisison about the number of product innovations is controlled by a discrete count variable (NIP).

The exogeneous variables are the following. SHARE is an indicator of the firm market power and is represented by the firm share of sales in its principal operating industry. Other measure of the relative dominant position of the firm is its size. TAMi (i=1,...,6) is a set of dummy variables corresponding to six intervals constructed using the number of employees as reported in the Data Appendix. However, in some specifications we have also tried a more aggregated classification: small-medium firms (less than 200 workers) and large firms (more than 200).[5]

The tangible capital stock (K) represents the replacement value of the firm's machinery capital stock and it is taken from Martin and Suárez (1996). The knowledge stock of a firm (G) is constructed as in [3] and represents the depreciated sum of past innovations. Related to this variable, we have constructed two measures of technological opportunity. One referred to the industry (produced knowledge stock, KPROD) and other referred to the firm (used knowledge stock). KPROD is the innovation produced at industry level taking into account the same process as that for G. The used knowledge stock is approximated by two variables: KUSED which is an accumulated stock of

[5] This last aggregation and the threshold is suitable for thc tipical spanish structure (Segura et al. (1993).

imported technology using the same depreciation rate as in [3], a 30%. The second variable, IMPTEC, is a dummy which reflects the import of some kind of technology in any given year. Additionally, two set of variables have been constructed (KUTi and GTi) to capture the influence of technological opportunity and knowledge by sizes on innovation activity. Both are constructed as the interactions among the six size intervals (TAMi) and KUSED and G, respectively.

A tipical variable employed to measure the market structure in the Structure-Conduct-Results paradigm is the concentration. We use a common index, CR4. It is constructed as the share of total industry sales represented by the largest four domestic firms. In this line, we also include two variables as proxies of environmental demand characteristics: IMP which controls if the firm imports in one year and IMP903, a non-time varying variable that controls if the firm imports during all period. Finally, in all specifications considered, time and sectoral shifters are included, as well.

3.3. Econometric models and estimation process

The usual model for the analysis of count data is the Poisson regression. However, an undesired feature of the model is the equality of the mean and the variance conditional on the explanatory variables. This equi-dispersion property generally appears as very restrictive in empirical applications. A negative binomial could be assumed for the data generating process to overcome the previous assumption (see Hausman et al. (1984)). The variable of interest I_{it} takes on only non-negative integers (the number of innovations) or assumes $1(I_{it}>0)$ with $1(A)$ indicating the occurrence of event A (whether a firm innovates or not). Under these circumstances, if I_{it} follows a Poisson distribution with mean λ, we can write the probability of k innovations carried out by firm i in year t as:

$$P(I_{it} = y / \lambda) = \frac{e^{-\lambda}\lambda^{I}}{y!} \qquad y = 0,1,2,... \qquad [9]$$

The negative binomial can be written as a compound of a poisson and a Gamma distributions. If we specify λ as a Gamma distribution and make the integration over λ, we obtain a negative binomial for I_{it} (see Cameron and Trivedi (1986) for details).

$$P(I_{it} = y) = \int_0^{\infty} P(I_{it} = y / \lambda) f(\lambda) d\lambda$$

$$= \frac{\Gamma(y+v)}{\Gamma(y+1)\Gamma(v)} \left(\frac{v}{v+\theta}\right)^{v} \left(\frac{\theta}{v+\theta}\right)^{y} \qquad [10]$$

being Γ a Gamma distribution with parameters *y* and *v*. The moments of the resulting negative binomial are:

$$E(I_{it}) = \theta, \theta > 0$$

$$Var(I_{it}) = \theta + \frac{1}{v}\theta^{2} \qquad [11]$$

Since θ > 0 the distribution derived in this way allows for overdispersion. Moreover, the term *v* permits to introduce a stochastic error term which captures unobserved heterogeneity and possible measurement errors. Finally, we could include conditioning variables through θ, *v* or both.

However, as we have emphasised in Section 2, the behaviour of Spanish firms regarding innovation activity, at least in a simple description, seems to follow a double decision process: one in which firm decides to carry out some kind of innovation (or dedicates some investment to these activities) and another one in which some product innovation takes place (the activity succeed). None of the previous models is correct if the process governing the discrete process (zero observations) is not the same as that taking account of the positive counts. Even when the same determinants appear as important in the two parts of the decision process, their effects and interpretations could be different.

The econometric specification closely follows the hurdle models for count data proposed by Mullahy (1986), also used in a demand model for health care by Pohlmeier and Ulrich (1995). Unlike Mullahy, we assume that the underlying distribution for the first stage is normal and we model that decision by a Probit. The second stage is governed by a negative binomial distribution. We also test for first hurdle dominance[6] which means that once a firm decides to carry out innovation activity, some product innovation takes place. This specification allows us to use different parameter sets for the data generating process in both decisions. If we denote by $\delta_1 = (\beta_1^{'}, \sigma_1^2)$ and $\delta_2 = (\beta_2^{'}, \sigma_2^2)$, the whole likelihood function can be written as:

$$L = \prod_{i \in \Omega_0} P(Y_{it} = 0 / X_{it}^{'} \beta_1, \sigma_1^2) \prod_{i \in \Omega_1} [1 - P(Y_{it} = 0 / X_{it}^{'} \beta_1, \sigma_1^2)] \prod_{i \in \Omega} [P(Y_{it} / X_{it}^{'} \beta_2, \sigma_2^2)] \qquad [12]$$

where the first term in [12] governs the binary decisison and the second the number of innovations once the first decision has been taken. Ω is the whole set of observations and Ω_0 and Ω_1 the subsets of zero and positive observations, respectively. This specification

[6] This is a concept proposed by Jones (1989).

allows for zero innovations once the decision to innovate has been taken. This collects, for instance, unsuccessful attempts to carry out product innovations.

On the other hand, a firm could decide to innovate and once taking this decision innovation takes place. This restriction could be introduced in model [12] by using a truncated distribution for the second hurdle. The likelihood for this model can be written as:

$$L = \prod_{i \in \Omega_0} P(Y_{it} = 0 / X_{it}^{'} \beta_1, \sigma_1^2) \prod_{i \in \Omega_0} [1 - P(Y_{it} = 0 / X_{it}^{'} \beta_1, \sigma_1^2)] \prod_{i \in \Omega_1} \frac{P(Y_{it} / X_{it}^{'} \beta_2, \sigma_2^2)}{P(Y_{it} \geq 1 / X_{it}^{'} \beta_2, \sigma_2^2)} \qquad [13]$$

While in model [12] we allow for the existence of zero innovations in the second hurdle, in model [13] the second hurdle is governed by a truncated binomial negative distribution. Both specifications, however, have been expressed as the product of two parametrically independent likelihood functions. All models presented above are estimated by maximum likelihood methods. The first part of both equations can be estimated by a Probit model and as a result we impose the restrictions of unit variance for the identification of the β_1 vector of parameters. Moreover, the Negbin I model (in Mullahy's terminology) permits both for under or overdispersion (see Cameron and Trivedi (1990)).

4. Empirical results

Table 4 presents the main results of the empirical analysis. Column 1 considers only the decision to innovate using a Probit regression whereas columns 2 to 4 pick up results considering the decision about the amount to innovate. Whereas in column 2 we report results of a Poisson, columns 3 and 4 correspond to those of a Negative Binomial regression. The difference in these last two columns refers to the restriction which the dominance concept imposes. Thus, results under column 4 present a first hurdle domince model. All specifications take only into account the relevant variables in terms of significance. As our main goal is to consider different behaviour in the innovative activities of the Spanish industry regarding firm's size, most of the variables have been interacted with size dummies.

The Probit coefficients offer interesting size and industry results. In general, all pure size effects are significantly different from zero which means that the overall effect is greater in the intermediate firms (those belonging to the interval 50-100 employees). In the decision to carry out or not technical innovation, the Schumpeterian hypothesis is not fulfilled by Spanish firms. This evidence also contradicts previous empirical results[7] where the conclusions pointed out towards more technical activity of dominant fims. Probably the main explanation of this fact could be the measure used for the technical change. Traditionally, the technical variable employed in several articles has been the R&D effort which is different to the used in this work: product innovation. It is clear that the expected size effect on innovation will not the same depending on the variable utilized.

Refered to the industries, it seems that firms which belongs to the Electrical sector have higher probability to introduce some product innovation than those in the remaining manufacturing sectors. Perhaps, it constitutes evidence that this sector offers more technical opportunities. For a better explanation of technological opportunity we need to interpret the coefficients of KPROD, IMPTEC and KUTi. The first variable

[7] Paricio (1993), Gumbau (1994).

presents the expected sign, but the other two have different behaviour. IMPTEC has a positive impact and reflects that the import of some kind of technology acts as an incentive to enforce some research activity within the firm, whereas the accumulated stock of imported technology (KUTi) reflects significantly shorter effects in small and big firms than in the reference category. The fact that knowledge industry variables enter with opposite signs could indicate complementarities in the production of innovation or rivalry effects as in Blundell et al. (1995).

On the other hand, the foreign demand variable has a positive impact on the decision to innovate, as expected. The knowledge stock has importance in the innovation probability but it seems that the greater effect corresponds to the fourth group, although the firms with few workers also have a certain influence.

The estimation of the count equations using Poisson and Negative Binomial models reveals similar behaviour in signs but neither in magnitude nor in significance of some conditionings.[8] Moreover, we could observe some remarkable shadings. Again, as Levin et al. (1985) expressed, when technological opportunity variables are included in the equation, the influence of concentration ratio on innovation desappears. Second, the market share does not seem to influence the decision or the amount of technical activities confirming our suspicious mentioned in the data section above.These results are confirmed in the Negative Binomial models but not in the Poisson specification. One explanation could be that the equi-dispersion restriction is not completely accomplished since the data reflects a variance which is significantly greater than the mean. In the

[8] Results in columns 3 and 4 correspond to the Negative Binomial coefficients of the Negbin Hurdle models presented in equations [12] and [13] of Section 3.3.

Negative Binomial models we have also modelled the parameter which allows for overdispersion with some of the conditionants.[9]

On the other hand, variables such as import penetration have no influence in this decision in contrast to the Probit results. Additionally, the pure or mixed effects of size variables are very different in the Poisson and the Negbin hurdle models, although the general conclusion is that all firms engage in less number of innovations than those belonging to the third group. Finally, the depreciated sum of knowledge stock, G, indicates a positive effect being the very small firms those that use more past innovation as capital stock. Probably, it is an indication that small fims have much more internal problems in the creation and adoption of technical changes than large ones, so they make profitable the innovation proposed in some previous period. This points out towards the necessity to consider two hurdles in the decision to innovate.

The final analyses conducted is presented in column 4. Results after introducing the first hurdle dominance restriction. This means that once a firm decides to innovate at the first stage, innovation takes place and we do not observe it at a corner in the second hurdle. We observe the same results as in the unrestricted model with the exception of concentration ratio which reveals how high market power could determine the decision of high amount of innovation once the decision to innovate has been already formulated. For the remaining variables are again in the magnitude of the coefficients although for their signs, the same comments apply.

Table 4 around here

5. Conclusions

[9] These results are not presented here but they are available from the authors on request.

Our analysis attempts to shed more light to the traditional question of the influence of market structure and firm size on innovations. The contribution of this approach drives in two ways. First, we use an alternative measure of technical change; in concret, the count of product innovation. which allows us to present more accurate estimates of the technical innovation variable. Second, we overcome the econometric problem derived of using the Poisson instead of the Negative Binomial procedure.

The information employed has allowed to check the hypothesis and carry out an econometric exercise taking into account the double decision process. Results seem to confirm a priori patterns. Moreover, the equidispersion property of the Poisson model reveals as very restrictive. Thus, earlier analysis without considering this hurdle specification could conduct to misleading inferences. We also obtain evidence that dominants firms do not necessary engage in a more dynamic product innovation. A confirmation of the unsignificant effect of concentration ratio is reported, as well. Finally, we get different behaviour of Spanish manufacturing firms by sector and size when considering the existence of two decisions as opposed to the results with univariate models.

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Table 1. Decision whether to innovate[1]		
	To innovate	**Not to innovate**
< 20 workers	26.8	27.8
between 21-50	22.2	21.8
between 51-100	9.5	7.2
between 101-200	7.7	7.9
between 201-500	22.3	23.0
> 501 workers	11.4	12.2
Total	21.3	78.7

Notes.
1. Figures are expressed in percentages over the totals.

Table 2. Decision about the innovation amount[1]			
	25% Decile	**50% Decile**	**75% Decile**
< 20 workers	2	3	5
21-50	1	3	5
51-100	1	2	8
101-200	1	2	5
201-500	1	3	6
>501 workers	2	9	8.5

Notes.

1. The intervals are 33% bottom, median and top of the distribution, respectively.

Table 3. Market Share and Innovation[1]		
Share[2]	Innovating	Non-Innovating
Small	4.93	20.07
Medium	15.82	56.75
High	0.51	1.92

	Innovation Activity[3]		
	Small	Medium	High
Small	1.47	2.58	0.88
Medium	4.10	7.84	3.89
High	0.08	0.20	0.23

Notes.

1. Figures are percentages of observations in 1990-93.
2. Share categories are constructed using the percentiles of the distribution. Small is the bottom quartile, Medium the median and High the top quartile.
3. The same as Share for Innovation Activity

Table 4. Maximum likelihood estimations[1]				
	Probit	**Poisson**	**Negative Binomial**	**Negative Binomial (only NIP>0)**
cte	-0.650 (0.11)	0.301 (0.07)	0.882 (0.23)	1.768 (0.16)
capbe (*10000)	0.677 (0.57)	0.451 (0.36)		
kprod	-0.011 (0.01)	0.015 (0.01)	0.038 (0.02)	0.032 (0.01)
imp903	-0.097 (0.09)	-0.242 (0.06)		
dimp	0.157 (0.09)	0.146 (0.06)		
imptec	0.302 (0.09)	0.566 (0.05)	0.649 (0.17)	
share		1.012 (0.43)	0.422 (1.72)	1.315 (1.14)
cr4		-0.457 (0.21)		0.508 (0.34)
chem	-0.130 (0.07)	-0.133 (0.05)		
elec	0.265 (0.09)	0.665 (0.05)		
machin		0.090 (0.06)		
food	-0.148 (0.08)			
tam1	-0.265 (0.11)	-0.168 (0.07)	-1.064 (0.24)	-0.313 (0.16)
tam2	-0.352 (0.11)	-0.381 (0.07)	-1.259 (0.25)	-0.461 (0.16)
tam4	-0.340 (0.15)	-0.568 (0.09)	-0.556 (0.27)	-0.448 (0.21)
tam5	-0.173 (0.11)	-0.484 (0.07)	-1.079 (0.25)	-0.487 (0.16)
tam6	-0.519 (0.13)	-0.612 (0.08)	-1.216 (0.31)	-0.388 (0.22)
dt92		-0.036 (0.04)	-0.481 (0.14)	-0.227 (0.09)
dt93	-0.064 (0.06)	-0.180 (0.05)	-0.774 (0.14)	-0.427 (0.10)
gt1	0.118 (0.01)	0.021 (0.00)	0.174 (0.03)	0.037 (0.01)
gt2	0.173 (0.02)	0.030 (0.00)	0.152 (0.04)	0.032 (0.01)
gt4	0.282 (0.06)	0.104 (0.01)	0.097 (0.01)	0.056 (0.01)
gt5	0.025 (0.01)	0.030 (0.00)	0.152 (0.03)	0.040 (0.01)
gt6	0.093 (0.01)	0.054 (0.00)	0.102 (0.02)	0.035 (0.01)
kut1	-0.284 (0.26)	-0.962 (0.07)	-0.603 (0.51)	-0.457 (0.49)
kut2		-0.005 (0.01)	0.005 (0.03)	0.237 (0.06)
kut4			-0.022 (0.01)	-0.011 (0.01)
kut5	-0.002 (0.00)		-0.003 (0.00)	0.003 (0.00)
kut6 (*1000)	-0.131 (0.11)	-0.077 (0.04)	-0.036 (0.13)	0.438 (0.28)

Notes.
1. Standard errors are in parenthesis.

Table A.1. Number of firms by size and industry[1,2]						
NON-INNOVATING FIRMS						
	Chem	**Elec**	**Machin**	**Food**	**Leather**	**Total**
< 20 workers	8.89	1.99	2.79	4.64	11.94	30.24
21-50	5.17	1.33	1.19	3.98	8.75	20.42
51-100	1.59	0.66	0.53	1.33	2.79	6.90
101-200	2.52	0.66	1.86	1.06	3.85	9.95
201-500	6.10	2.79	3.32	3.32	5.04	20.56
> 501	3.45	1.46	2.39	2.92	1.72	11.94
Total	27.72	8.89	12.07	17.24	34.08	100
INNOVATING FIRMS						
	Chem	**Elec**	**Machin**	**Food**	**Leather**	**Total**
< 20 workers	5.96	2.13	2.13	3.40	13.62	27.23
21-50	4.26	1.28	1.70	3.83	9.79	20.85
51-100	2.13	3.40	1.70	1.70	2.55	11.49
101-200	2.13	2.13	1.70	0.43	2.55	8.94
201-500	5.11	2.98	2.98	3.83	6.38	21.28
> 501	1.28	2.98	2.55	2.13	1.28	10.21
Total	20.85	14.89	12.77	15.32	36.17	100

Notes.
1. Figures are expressed in percentages for 1993.
2. The 18 sectors of NACE-CLIO classification have been aggregated to 5 since the analogy presented among the coefficients of industry dummies.

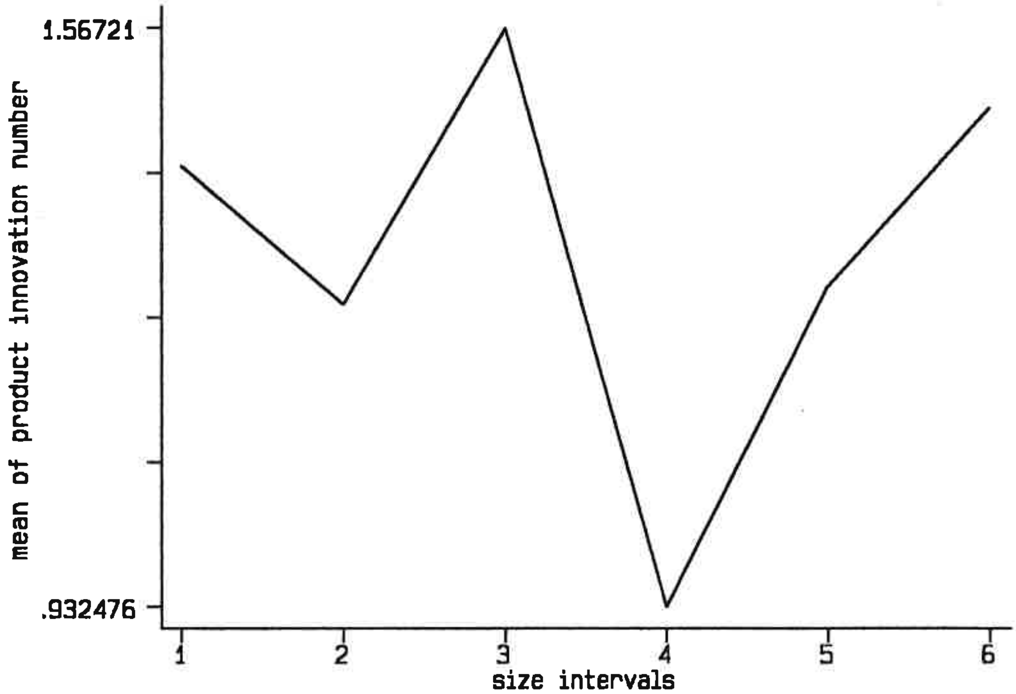

Figure 1. Count of product innovation average by size

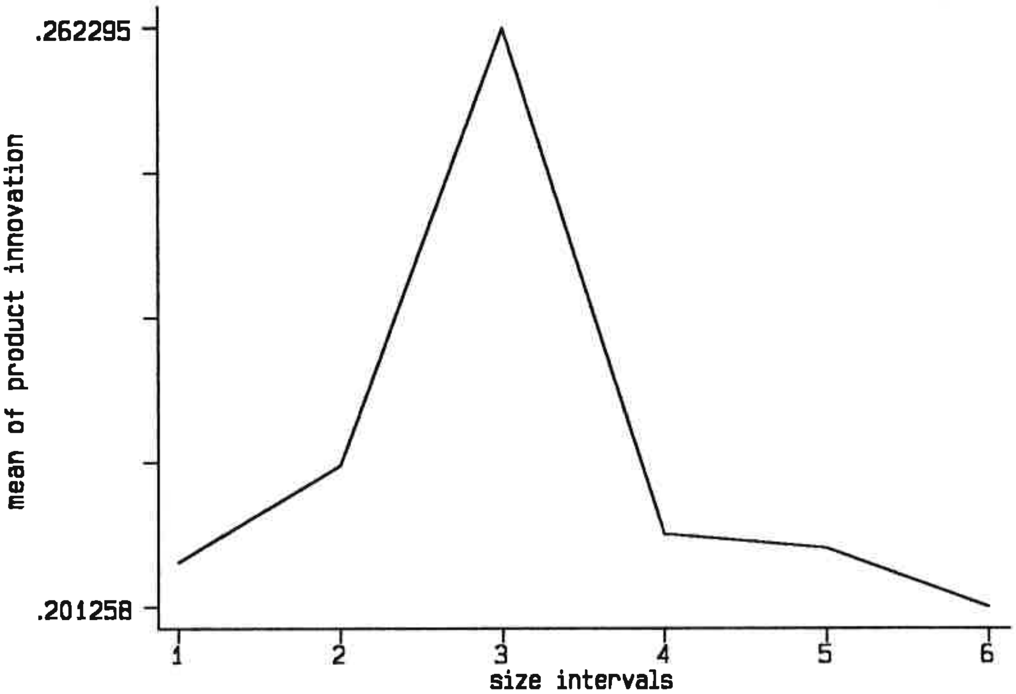

Figure 2. Product innovation average by size