EXPLAINING THE DECISIONS TO CARRY OUT PRODUCT AND PROCESS INNOVATIONS: THE SPANISH CASE

ESTER MARTINEZ-ROS
Universidad Carlos III de Madrid

We investigate the determinants of innovation activity making a distinction between product and process innovations. We analyse a pseudo production function of innovations where among the explanatory variables, special attention is paid to firm and market characteristics. The study is applied to a large sample of Spanish manufacturing firms during the period 1990–1993. There are important implications arising from the empirical results: 1) Product and process innovations are intimately related independently of the model used in the estimation. 2) The control by unobserved firm effects as the ability and experience of manager is so important as to affect the conclusions on the managerial decisions about which type of innovation develop. 3) Given the feedback effects amongst innovation decisions and other factors determining them, it is also very important to consider a version of the model that allows correlation among those unobserved effects and explanatory variables. 4) The probability to innovate is higher in capital intensive firms and in firms with export activities. 5) Market competition encourages the decision to innovate up to a threshold. vi) The past firm experience and the managerial quality play a significant role in the probability to innovate. vii) Product and process innovation decisions are complementary.

INTRODUCTION

This paper investigates the determinants of innovation activity in a large sample of Spanish manufacturing firms during the period 1990-1993. A distinction is made between product and process innovations and, among the explanatory variables, special attention is paid to firm and market characteristics. The analysis incorporates some important differences regarding to previous works in this field. On the one hand, we distinguish different kinds of innovations. On the other, the use of panel data allows us to control for unobserved firm heterogeneity, that is we focus on the role of unobserved managerial effects and its effects on the decision to innovate.

The reasons for the presence and intensity of innovation activities in firms and industries have received a lot of attention in the economic literature during the past 50 years. Most of this research tries to expand the line opened by Schumpeter (1942). As it is well known, the Schumpeterian hypotheses look at firm's characteristics (mainly its size as a source of internally generated financial resources) and at the characteristics of the market (mainly the degree of competition) as the principal determinants of innovation activity by business firms. Therefore, most of the post Schumpeterian empirical research has focused in trying to test whether larger firms in markets with "not too much" competition innovate more than the rest of firms (see Levin et al., 1985, Kamien & Schwartz, 1982; and Symeonidis, 1996 for complete surveys of this empirical literature).

Our research in this paper introduces several distinct features in relation to previous works. First, we measure innovation activity in terms of outputs rather than in terms of inputs. We count as innovation the report by each firm in the sample that such activity has actually taken place. Therefore, not only patented innovations are considered. We believe that the report of product or process innovations is a more complete indicator of innovative activity than the use of the number of patents, since there are many innovations that are introduced without being patented. Moreover, with these measures we proxy better the structural features that originate the adoption of innovations by an organisation (Daft, 1978; Moch & Morse, 1977).

Second, among the explanatory variables we include a measure of technological capital which, in fact, implies the estimation of an implicit "production function" of innovations. The stock of technological capital is constructed using a permanent inventory model of R&D expenditures over time, with an exogenously given depreciation rate. So, our approach is in line with Hall and Mairesse (1993) or Crepon and Duguet (1997) and in contrast with Bound et al. (1984), Hall et al. (1986) or García-Montalvo (1993) which use lagged R&D expenditures as inputs, without taking into account an explicit depreciation rate of capital. Since previous work with Spanish data has looked at inputs rather than outputs as indicators of innovation activity, there was no opportunity for estimating production functions.

Third, we consider technological research as a heterogeneous activity that gives place to distinguish both, product and process innovations. In general, process innovation will be cost reduction driven, while product innovation is more likely to be oriented towards product differentiation. Then, one would expect that each type of innovation will be affected in a different way by the explanatory variables (Lunn, 1986; Kraft, 1990). Moreover, we can test whether each type of innovation is independent of the other or, to the contrary, they are jointly determined activities. Our study, however, departs from other evidence in two ways. First, because of the availability of panel data; second due to the definition of the technological variable. Panel data allows us to use estimation methods that try to overcome possible biases derived from the omission of relevant unobserved firm specific factors among the explanatory variables. In that sense, we set up the possibility that the ability of managers influence the extent to which the innovation is adopted (Amabile, 1983; Leonard-Barton & Deschamps, 1988). However, although the expectation firms tend to innovate more if manager behaviour is good , there exist some evidence that distinguish the different effects according to different types of innovations (Zmud, 1984). In terms of definition, we distinguish product from process innovations instead of using others measures—incremental versus radical, for instance, of Ettlie, Bridges, and O'Keefe (1984), Deward and Dutton (1986) or Brouwer and Kleinknecht (1998)— because we focus on the output of innovation rather than on the success of its adoption and because of data limitations.

Fourth, the data used is drawn from the *Survey of Business Strategies* (ESEE) provided by the Spanish Industry and Energy Ministry for the period 1990-1993. Hence, we can follow the same firms over time in each year of the period. This allows us to construct a balanced panel of data and to carry out an empirical exercise using a double estimation process. At a first stage, we estimate separately pooled Probits attending to the two types of innovation and assuming that both, innovation in process and innovation in product, are not related to each other. Second, we estimate random effects Probit models. In this case, we consider the existence of heterogeneous firm effects that could be related with the explanatory variables. Moreover, we test whether product innovations affect the probability to innovate in process and vice-versa.

There are important implications arising from the empirical results of the paper. On the one hand, those related to the statistical procedures used to approach the problem. They confirm three issues: 1) Product and process innovations are intimately related. 2) The control by unobserved managerial effects is so important as to affect the conclusions on the effects of almost all variables in the model. 3) Given the feedback effects amongst innovation decisions and other factors determining them, it is also very important to consider a version of the model that allows correlation among unobserved managerial effects and explanatory variables. Second, the results have several economic consequences: 1) The probability to innovate is higher in capital intensive firms and in firms with export activities. 2) Market competition encourages innovation up to a threshold. 3) The past firm experience and the managerial quality play a significant role in the probability to innovate. 4) Product and process innovation decisions are complementary.

The paper contains 4 sections in addition to this introduction. The theoretical framework is presented in Section 2. Section 3 briefly describes the data used and presents the empirical specification and the measurement of the variables. Section 4 reports comparisons amongst the results obtained by the different econometric models, together with the tests of such models. Discussion of results jointly with some policy implications are reported in Section 5, where we also provide a summary of the main conclusions.

THEORETICAL FRAMEWORK AND HYPOTHESES

The reduced equation model to be estimated explains the expected innovation decision as a function of the stock of technological capital at the beginning of the period, of the technological opportunities offered by the market and of other variables which refer to firm and market characteristics,

$$E(I_{it}) = f(G_{it-1}, \tau, X_{it-1}) \qquad [1]$$

where I is an innovation indicator, G is the technological capital, τ indicates technological opportunities and X is the rest of explanatory variables.

Equation [1] can be derived as a result of a dynamic optimisation model in which firms decide on physical inputs, labour and capital and on innovation decisions, maximising its market value determined by the present value of future cash-flows; see Reinganum (1989) and Blundell et al. (1995) for further details. However, more theoretical analysis and explanation is needed to postulate which are the actual variables in X and how are they expected to determine the dependent variable. Following the argument of Schumpeter (1942), we find important in the determination of R&D projects two variables: firm size and market concentration. First, one expects a positive relationship between firm size and R&D. Second, with a high market concentration firms find profitable to engage in R&D. Both hypotheses have been analysed in theoretical and empirical terms obtaining contradictory results.

Our objective is to include both hypotheses in the X determinants of the innovation equation. In fact, we are able to group these determinants into characteristics of the firm (size, physical capital, degree of capital or price elasticity of demand) and market conditions (degree of competition).

We expect that the technological capital G_{it-1} will have a positive effect on the innovation activity, captured by I_{it}, since the search effort which determines G_{it-1} is intended precisely to be able to improve products and processes. In fact, equation [1] may be interpreted as a production function of innovations where G_{it-1} is a measure of the input, and τ, X_{it-1} are proxies which influence the strategic decision to improve or not products/processes as the market and firm conditions evolve.

Industries with more technological opportunities are expected to encourage innovation activity since the accumulated knowledge, mostly shared by many of the firms due to spillovers or other effects, reduces the cost of translating knowledge into new products and processes. But at the same time, it may work against innovation if the innovating firms consider that the innovation will be imitated by a rival in a short period of time. So, the net effect is uncertain.

H1: More technological opportunities in the sector, encourage firms to develop innovation activity.

For a given stock of technological capital and opportunities, the *size* of the firm may influence the output of innovations due, for example, to differences in other physical, human and financial resources across firms with different size. In general, a positive effect of size on innovation output is expected, since larger firms tend to be less financially constrained. However, it may also happen that larger firms view themselves as less threatened by competition and lower the rate of innovation in order to not to erode profits of current products and processes. Besides, if the firm has monopoly profits, the incremental profits of innovation will tend to be relatively lower than in a firm facing more competition.

Previous empirical research has tested the effect of size on innovation activity with mixed results but, in many of the cases, innovation activity was measured in terms of inputs rather than outputs.[1] The apparent disarray in obtaining consensus of the effect of firm size on innovation activity responds, in many cases, to the omission of many controls of firm and market characteristics despite the demonstrated importance of such effects (Scott, 1984). The size distribution of firms varies across industries, in part because of differences in the degree of scale economies in production and distribution. Thus, there is a good reason to believe that fixed industry or firm effects are correlated with firm size and that the omission of such effects will bias the estimates of the effects of size on innovation. Similarly, firm characteristics such as diversification and some measures of financial capability are correlated with firm size. So, in order to isolate the size effect on innovation for a given knowledge stock is important to control for market competitive conditions and other firm features.

H2: Large firms have more opportunities to engage innovation activity.

The characteristics of the production technology may also affect the decision to introduce innovations for a given stock of technological capital; one variable used to differentiate production technologies is the *intensity of physical capital*. Firms with more capital intensive technologies will tend to innovate more if, as expected, the rents of innovation are less threatened as, to exploit the innovation, high investment in physical capital is required. It may also happen that more capital intensive processes provide less room for innovation since they are more automated and rigid. The final effect of capital intensity on innovation activity is uncertain. Kraft (1990) included only the capital intensity in the product equation obtaining a positive effect.

H3: More capital intensive firms tend to innovate more.

Production processes may also be differentiated in terms of the *degree of vertical integration*. As firms internalise more activities there are more opportunities to innovate, all the rest equal, and probably there are more incentives to do it if the results of innovation can be spread over several activities. Although little quantitative work has been done in this area, some case studies suggest the presence of economies of scope to R&D in vertically related industries. Malerba (1985) studied the life cycle of technology in the semiconductor industry and found that the advantages of vertical integration for innovative activity had varied along the cycle.

H4: More vertical integrated firms have more opportunities to innovate.

Another variable, which has been related to innovation activity, is the *price elasticity* of demand faced by the firm. As Kamien and Schwartz (1970) showed, the gains from reducing the cost of production (process innovation) increase as the price elasticity of demand also increases, in absolute value; but for a given level of technological capital, the opportunities to innovate may be lower if the production process is highly standarised. On the other hand, firms with more homogeneous products (and therefore with many substitutes) may have more opportunities and incentives to try to introduce product innovations in order to differentiate the product and soften competition (Spence, 1975).

H5: With an inelastic demand innovating firms prefer to engage in process innovations while with an elastic demand they prefer to carry out product innovations.

Finally, the effect of *competition* on innovation activity could also have different signs, given a knowledge stock. The Schumpeter's proposition supports that firms in concentrated markets can more easily appropriate the returns from innovations while Arrow's hypothesis arguments that firm's gains from innovation are larger in a competitive industry than in a monopolistic one. This discussion suggests that there are many theoretical issues, which will have to be tested empirically in order to know the sign of the net effect of the explanatory variable. The lack of a clear theory also reinforces the importance of using econometric estimation procedures that minimise estimation biases. Acs and Audretsch (1987) found that large firms are more innovative in concentrated industries with high barriers to entry, while smaller firms are more innovative in less concentrated industries that are less mature. Blundell et al. (1995) obtained that innovation activity increases with market share and decrease with market concentration. Therefore, in the long run an increase in market share may have a net negative effect on innovation if it also increases market concentration.

H6: Market competition conditions positively the innovation activity.

RESEARCH DESIGN

Data Description

The data set corresponds to the ESEE conducted over the period 1990-1993 and surveying over approximately 2,000 firms every year. The survey is an attempt to know the characteristics of firms belonging to the Manufacture sector, so we are available information about markets, customers, type of products, levels of employment, trade and technological activity. It has appeared as an alternative database existing in Spain in terms that it collects information of firms instead of sectors or establishments. This is an unbalanced 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. To offer a brief description of this survey we use two indicators: production activity and firm size.

The production activity refers to industries whose firms belong to and the classification corresponds to the NACE-CLIO.[2] Although this classification groups firms into 18 manufacturing sectors, we have aggregated them to 5 for the purposes of the analysis. The size aggregation is constructed using the number of employees at December 31. It implies that temporary workers have been weighted by the period they have been hired by the firm. The ESEE uses specific size intervals: less than 20 workers, between 21 and 50, between 51 and 100, between 101 and 200, between 201 and 500, more than 500. Both the industry classification and the size intervals

TABLE 1
Number of firms by size and industry[1,2]

	INNOVATING FIRMS					
	Chem	*Elec*	*Machin*	*Food*	*Leather*	*Total*
<20 workers	76	25	27	35	107	270
21–50	78	27	14	34	134	287
51–100	27	23	13	19	43	125
101–200	39	18	19	17	45	138
201–500	132	59	90	74	128	483
>501	71	40	74	67	25	277
Total	423	192	237	246	482	1580
	NON-INNOVATING FIRMS					
	Chem	*Elec*	*Machin*	*Food*	*Leather*	*Total*
<20 workers	217	52	63	137	345	814
21–50	138	28	50	118	244	578
51–100	45	20	11	35	67	178
101–200	40	15	31	18	59	163
201–500	110	48	53	73	112	396
>501	51	41	23	37	31	183
Total	601	204	231	418	858	2312

Notes.
1. Innovating firms are those which engage product innovation, process innovation or both innovations at the same time.
2. The 18 sectors of NACE-CLIO classification have been aggregated to 5 in order to simplify the Table.

are constructed keeping on the sample representativeness as we can observe in Table 1.

This Table presents a cross tabulation of the sample using industry and firm size as controls and distinguishing innovating from non-innovating firms.[3] During this period, we have 40% of firms undertaking some innovation activity (*only* in product, *only* in process and *both* product and process). This description allows us to assess that the most dynamic sectors within the innovative subsample are *Chem* and *Leather*. In general, large firms (more than 200 employees) innovate more although we observe an important role of the very small group in developing some technological advance. Almost in all innovator sectors, large firms carry out R&D activities with the exception of the *Leather* industry, where companies with less than 50 workers have higher activity.

In Table 2, we present mean values for the two innovation activities according to industry classes and firm size (aggregating size intervals into firms with 200 or fewer workers and those with more than 200 workers). Moreover, we dissagregate those firms which only engage in one of these activities from those which do both simultaneously. In general, column 6 (which reports aggregated figures) shows no differences in size when firms *only* innovate in product, while large firms present clearly higher figures when they *only* innovate in process. However, when we observe figures by sectors the behaviour is rather different. In terms of *only* product innovation, we do not observe a similar pattern attending to size and industries. For instance, small firms of *Elec*, *Machin*, or *Leather* industries innovate in product,

TABLE 2
Frequency of Innovation Activity[1]

	Chem	*Elec*	*Machin*	*Food*	*Leather*	*Total*
			Only Product Innovation			
Small	0.077	0.183	0.114	0.056	0.110	0.099
Large	0.110	0.074	0.075	0.127	0.054	0.090
			Only Process Innovation			
Small	0.153	0.135	0.088	0.121	0.116	0.125
Large	0.225	0.090	0.271	0.140	0.233	0.200
			Product and Process Innovation			
Small	0.103	0.130	0.118	0.077	0.089	0.097
Large	0.223	0.362	0.337	0.295	0.230	0.278

Notes.
1. Figures are mean values for the frequency of innovation by size and sector.

on average, almost double than large firms in the same industries. In contrast, large firms of *Chem* and *Food* develop more product innovations than small ones. In relation to firms *only* innovating in process, large firms innovate more in almost all industries with the exception of *Electrical products*.

When companies carry out both process and product innovations simultaneously, large firms engage more R&D activities as regards the last row. In some cases, the relative frequency is three times larger than that corresponding to small firms (i.e. figures corresponding to *Elec* or *Machin*). This pattern suggests that depending on the type of innovation activity developed by the firm, the conclusions about the effects of the determinants can be very different, at least for some determinants at this very simple descriptive stage.

METHODOLOGY

The empirical model postulates a functional relation between innovation activity and some explanatory variables which in this paper are grouped into characteristics of the firms and characteristics of the markets in which the firm operates.

As it has already been mentioned, innovation activity is measured in terms of output, and particularly in terms of a discrete variable that takes the value of 1 if the firm has innovated in period t, and 0 otherwise. Furthermore, a distinction is made between innovations in product and innovations in process. Each type of innovation is expected to respond differently to the explanatory variables, and therefore there will be two empirical models to be estimated. Previous papers on this topic[4] have pointed out that technological research and innovation can be directed towards product or process innovation, but not necessarily towards both. This, however, has been ignored most of the time in empirical work, where innovation has been considered as an homogeneous activity.

Another important issue is whether there may be some interdependencies between process and product innovations, in the sense that when firms introduce a new product in the market, there will also be a need to improve the production process. The empirical model will allow for such possible interdependencies.

Since our database contains information about the kind of innovation (product or process) that the firm engages on, we can separate the innovation output into these two types. The empirical treatment of the innovation indicator equation [1] could drive to the estimation of two different specifications: one referred to product and another one referred to process innovation:

$$IPROD^{*}_{it} = \alpha_0 G_{it-1} + \alpha_1 \tau + \alpha_2 XFIRM_{it-1} + \alpha_3 XMARKET_{it-1} + \varepsilon_{it} \qquad [2]$$

$$IPROC^{*}_{it} = \beta_0 G_{it-1} + \beta_1 \tau + \beta_2 XFIRM_{it-1} + \beta_3 XMARKET_{it-1} + \upsilon_{it} \qquad [3]$$

where $IPROD_{it} = 1$ if $IPROD^{*}_{it>0}$, and $IPROD_{it} = 0$ otherwise, in the first equation and $IPROC_{it} = 1$ if $IPROC_{it} > 0$, and $IPROC_{it} = 0$ otherwise, in the second equation. The error terms have the following structure $\varepsilon_{it} = \eta_i + u_{it}$ and $v_{it} = \mu_i + w_{it}$ with u_{it} and w_{it} satisfying standard conditions. Moreover, the dependent variables are simple indicators (dummy variables) of whether or not a firm engages in product and/or process innovation. Moreover, we are interested in checking whether the development of process innovations affects the probability of innovating in product and vice-versa. Consequently, we estimate both equations introducing the alternative lagged innovation indicator ($IPROC_{it-1}$ in equation [2], $IPROD_{it-1}$ in equation [3]).

Notice that innovation activity is conditioned on the technological capital stock of the firm G_{it-1}. This implies that equations [2] and [3] can be interpreted as production functions of innovations, where *XFIRM* and *XMARKET* are explanatory variables of the innovation activity of the firm, for a given capital stock. Some of the firm and market characteristics included in *XFIRM* and *XMARKET* may also affect the capital stock G_{it-1}, i.e., this stock is also endogenous. To account for this, G_{it-1} will be instrumented by its prediction $GINST_{it-1}$. We construct *GINST* regressing G_{it-1} on industry dummies, time dummies, firm characteristics, market characteristics and the past knowledge stock under the assumption that the error term is not autocorrelated.

We are going to address the different questions posed in this paper in two steps. First, we implement individual discrete choice models for a general innovation indicator and for each innovation decision. This allows us to check whether dissagregating different kinds of innovations matter. In this approach, we do not consider the possible influence of unobserved heterogeneity, but we only estimate pooled probit models. In a second step, we try to overcome such problem, by estimating single probit models controlling for the presence of unobserved firm effects as managerial ability, experience, or other factors that remain constant along the period. We also allow for the potential cross-effects of both innovation types.[5] Details of the econometric procedure are reported in Martínez-Ros (1998).

MEASUREMENT OF THE VARIABLES

The indicator variables follow the observability rules: *IPROD* takes value 1 if firm carry out product innovations and zero otherwise and *IPROC* takes value 1 if firm develop process innovations, and zero otherwise.

The technological knowledge stock (G) captures previous R&D effort done by the firm affected by a depreciation rate. It is constructed as:

$$G_{it} = S_{it} + (1 - \delta)G_{it-1} \tag{4}$$

where S_{it} is the R&D expenditure of firm i in period t and δ is the depreciation rate.[6] This specification basically follows the reasoning of Griliches and Mairesse (1984) or Hall (1990) in the sense that all search contributes towards the innovation stock by generating a constant stream of incremental innovations. This search process story is called *leaky bucket* and implies that the decision about innovating (or the number of innovations obtained) evolves according to the indicator function [1] (or a count equation when I_{it} is observed).[7]

Technological opportunity, τ, reflects the influences of technological push in the industry (Lunn, 1986). We approximate it using the industry knowledge stock minus the own firm R&D expenditure (*SPILL*). It is constructed using [4] where S refers now to R&D expenditures at industry level normalised by the industry sales net of firm sales. Notice that it captures an externality of R&D capital as Crepon and Duguet (1997) pointed out. The sign of the coefficient of this variable in the empirical model is ambiguous, since in an industry with high level of R&D activity there will also be more spillovers which may facilitate the innovation activity; but it may also happen that firms are in advantageous positions to imitate the innovations of other rivals in the industry and if this is the case, innovation activity may be showed.

The *XFIRM* vector includes a list of characteristics of the firm which may influence the decision to innovate, for a given technological capital of the firm: size, production technology, vertical integration, export activity and foreign ownership.

Size of the firm is measured by the natural log of the number of employees (*LnEMP*). In general, larger firms will have more complementary resources of the technological capital (financial, physical, commercial, . . .) and therefore, a positive effect of size in the probability of innovation is expected, both in product and in process. However, larger firms may be subject to more bureaucratic controls and dysfunction which may affect negatively their capacity to translate capital stock into innovations. Moreover, if size is positively associated with market power, the incremental benefits of innovation may be relatively lower for larger firms than for smaller ones (Pavitt et al., 1987) and, specifically, could influence more in product innovating firms than in process innovating firms.

The *production technology* is proxied by the ratio of sales to fixed assets of the firm (*KSA*).[8] A higher value of the ratio means that the production process is relatively more capital intensive. More capital intensive process may make more difficult to improve current product and process, because the production process is less suitable for adjustments and manipulations than in more labour intensive technologies. On the other hand, the introduction of new production technologies gives the opportunity to change current products and processes and therefore to innovate. So, the actual relation between capital intensity of the production process and innovation activity may be considered an empirical issue.

The *degree of vertical* integration of the firm will be measured, inversely, by the ratio of purchases to other firms divided by the total value of production, both variables defined in a yearly basis (*CISP*). As we indicated above, as the firm performs more activities internally, there are more opportunities to innovate and therefore a negative sign of the variable *CISP* is expected.

A dummy variable (*DEXP*), which takes the value of 1 when the firm exports and 0 otherwise, is used to describe the *export activity* of the firm. We expect that export activity favours innovation, as their presence in foreign markets may require more innovations in order to be competitive. But it is also true that firms with more innovation activity may have more incentives to export since they also have more intangible resources to sustain growth. So, no clear direction of the causality may be established.

Finally, a dummy variable (*CAPEXT*) is used to indicate if the firm is controlled by *foreign* ownership (50% or more). This is a control variable for which no clear sign can be expected from the theory.

On the other hand, the *XMARKET* variables pick up industry shifters, which try to characterise the market structure.[9] We will refer first to the degree of competition in the product market proxied, inversely, by market concentration. In general, the empirical evidence supports Schumpeter's arguments that firms in concentrated markets can more easily appropriate the returns from inventive activity. Others works find evidence that market concentration do not promote R&D because the expected incremental innovating rents are larger in competitive markets than under monopoly conditions (Arrow, 1962; Bozeman & Link, 1983). The discussion about the right sign of this variable needs to be related to the endogeneity of the measure used in the empirical analysis, i.e. the concentration ratio. As Levin and Reiss (1984) and Levin et al. (1985) showed, the endogeneity of concentration produces biases in the estimates of the effect over innovation activity. To avoid the possible endogeneity bias of the concentration variable, the intensity of market competition will be approximated, in an inverse way, by the average gross profit market of the industry (*AVGMBE*), in order to capture whether market competition encourages innovation activity. A positive sign would give support to Schumpeter's hypothesis while a negative sign would be in accordance with Arrow's predictions. The introduction of this variable in both innovation equations also allows us to test for different effects of market competition in product and process innovation (Lunn, 1986; Kraft, 1990).[10] We include the squared of gross profit market (*AVGMBE2*) in order to capture possible non-linearities in the market competition.

Another characteristic of the market that may affect innovation activity is the *growth of demand* (Schmookler,1966). A dummy variable *RECES* is defined which takes the value of 1 when the market of the firm is in a recession and 0 otherwise. The theory predicts that growth of demand encourages innovation and therefore a negative coefficient for *RECES* is expected.

The *homogeneity of product* is captured by a dummy variable (*EP*) that takes the value of 1 when firm produces a standard product and 0 otherwise. This variable is proxying the elasticity of demand because standard products are viewed as homogeneous products and, hence, with a more elastic demand. The theory suggests that the production of product innovations needs to elastic demands (Spence, 1975), while the production of process innovation enhances with inelastic demands (Kamien & Schwartz, 1970).

Finally, we control possible shocks common to all industries using time dummies. We also control time invariant firm effects in the models estimated using the panel nature of the data. The unobserved effects η_i and υ_i would be recovering managerial quality, firm experience in doing R&D activities, ability in internal organisation, etc., in the production of innovations. We expect for example, that higher quality in the management, higher probability to innovate.

TABLE 3
Probits Results (Pooled Data)[1,2]

Dependent Variable:	*INNOVA*	*IPROD*		*IPROC*	
Intercept	−1.012	−1.574	−1.540	−1.260	−1.266
	(4.06)	(5.88)	(5.67)	(4.94)	(4.88)
$IPROD_{t-1}$					0.454
					(7.66)
$IPROC_{t-1}$			0.518		
			(8.72)		
KSA_{t-1}	−0.005	−0.007	−0.006	−0.004	−0.003
	(3.29)	(2.85)	(2.78)	(2.28)	(2.07)
$GINST_{t-1}$	0.206	0.351	0.370	0.037	0.021
	(2.68)	(4.01)	(4.20)	(0.41)	(0.23)
$SPILL_{t-1}$	−0.012	0.008	0.007	−0.011	−0.010
	(0.32)	(0.20)	(0.20)	(0.29)	(0.26)
$DEXP_{t-1}$	0.461	0.513	0.482	0.264	0.202
	(7.75)	(7.91)	(7.33)	(4.28)	(3.22)
$AVGMBE_{t-1}$	0.050	0.061	0.060	0.036	0.033
	(1.45)	(1.63)	(1.58)	(1.02)	(0.94)
$AVGMBE2_{t-1}$	−0.256	−0.345	−0.335	−0.162	−0.141
	(1.81)	(2.20)	(2.11)	(1.11)	(0.96)
$InEMP_{t-1}$	0.141	0.106	0.069	0.192	0.179
	(6.83)	(4.93)	(3.13)	(9.11)	(8.39)
EP_{t-1}	0.006	0.236	0.275	−0.176	−0.200
	(0.12)	(4.07)	(4.68)	(3.27)	(3.69)
$RECES_{t-1}$	−0.092	−0.106	−0.114	−0.108	−0.105
	(1.67)	(1.76)	(1.88)	(1.88)	(1.82)
$CAPEXT_{t-1}$	−0.014	0.015	0.019	0.021	0.018
	(0.20)	(0.22)	(0.27)	(0.31)	(0.27)
$CISP_{t-1}$	−0.129	−0.151	−0.132	−0.145	−0.131
	(1.03)	(1.20)	(1.02)	(1.14)	(0.99)

Notes.
1. All estimations include time dummies.
2. t-ratios in brackets

FINDINGS

We try to answer the questions posed in the previous sections of this paper using the estimation methods outlined above. It is important to notice that the interpretation of the obtained results will be different if we control for unobserved firm effects or not. These heterogeneous effects are considered random along the different specifications because of the number of firms involved in the exercise. It is reasonable to think that if these variables (for instance, managerial ability) are important in the decision to innovate, falling to control them would provide inconsistent parameter estimates. However, the pooled probit results of Table 3 should still be consistent if firm specific effects do not matter. But this is not a plausible assumption in a model that determines innovation frequencies. In order to take account of this fact, we estimate random effects probit models whose results are reported in Table 4. Moreover, we test whether product and process innovations are independent of each other.

TABLE 4
Probits Results (Panel Data)[1]

Dependent Variable:	*IPROD*	*IPROC*
$IPROD_{t-1}$		0.262
		(24.9)
$IPROC_{t-1}$	0.278	
	(26.5)	
KSA_{t-1}	0.005	0.003
	(6.76)	(3.44)
$GINST_{t-1}$	0.263	0.002
	(27.9)	(0.18)
$SPILL_{t-1}$	0.011	−0.079
	(1.85)	(14.5)
$DEXP_{t-1}$	0.174	0.108
	(9.27)	(6.34)
$AVGMBE_{t-1}$	0.059	0.039
	(10.5)	(7.61)
$AVGMBE2_{t-1}$	−0.306	−0.191
	(13.5)	(9.27)
$\ln EMP_{t-1}$	0.041	0.185
	(2.07)	(10.3)
$RECES_{t-1}$	−0.068	−0.074
	(6.46)	(7.76)
$CAPEXT_{t-1}$	−0.031	−0.123
	(1.06)	(4.63)
$CISP_{t-1}$	−0.193	−0.122
	(7.72)	(5.40)

Notes.
1. t-ratios in brackets.
2. Random effects probit model (correlation amongst effects and variables; i.e., two stage within-groups using Chamberlain's method). Heteroscedasticity allowed.

We are interested in answering the following questions. First, we like to test whether estimating pooled discrete choice models on total innovations produces different results from those obtained considering each type of innovation separately. We use univariate probit models without controlling for heterogeneity to conduct these tests. Second, we would like to test the simultaneity between both types of innovation.[11] If managerial ability is correlated with physical capital stock, for example, we will get biased estimates. Moreover, this is going to happen in the presence of feed-backs amongst innovation decisions and explanatory variables.

Our first concern is about the homogeneity between the models that explain product and process innovations. Table 3 presents the probit results of three empirical specifications, which allow us to test for such hypotheses. The second issue is about the simultaneity between the two innovation activities. The results of Table 3 confirm such simultaneity where past process (product) innovation indicator affects the probability of current product (process) innovation. Finally, the last concern is about the relevance of the firm specific effects.[12] The results presented in Table 4 introduce firm specific effects in the probit estimation under the assumption that the effects are random and correlated with the other explanatory variables. The more general specification of the models with fixed effects justifies that we take the results of Table 4 as the relevant ones to test the theoretical predictions. However, it will also be econometrically and economically relevant to understand the discrepancies between the results presented in the different tables.

In addition, to interpret the differences among the results in Tables 3 and 4 in terms of correlation among unobserved and observed variables, we must also bear in mind that the within groups procedure transforms the variables to differences from firm time means. Therefore, as regards the pooled models, the within groups results indicate whether changes in variables at the firm level affect the innovation decisions.

Table 4 report results allowing for heteroscedasticity and correlated effects. Notice that those results are provided using the within-groups transformation (in order to rule out the effects) after obtaining reduced form predictions for the innovation decisions. Therefore, as a consequence of within groups transformation, all variables without time variation are also ruled out while estimating. On the other hand, the correlation amongst effects and variables is confirmed while estimating the reduced form models.[13]

We must look carefully at the results in Tables 3 and 4 for two reasons. First, results do not directly evaluate the effects on innovations of their main determinants. Second, specifications [2] and [3] are the indicator counterparts of the production functions of innovations, conditional on a given level of technological stock. Consequently, the coefficients should also be interpreted conditional on these levels. Given the first reason above, we provide in Table 5 the marginal effects of each variable on innovation probabilities, *ceteris paribus*.

DISCUSSION AND IMPLICATIONS

Given the comments on the preceding section, we can focus on the discussion of the main results reported in Table 4. In particular, we concentrate on whether we reject or fail to reject the hypotheses set up in the theoretical model. Moreover, we also compare these results with the alternative specifications (Table 3) in order to illustrate how the omission of the correlation amongst firm specific effects and other explanatory variables affects the estimated coefficients. The expected result that innovation cannot be seen as a homogeneous activity is clearly confirmed in Table 3. Both types of innovations are determined in a different way, for the case of Spanish manufacturing firms. For a given technological stock, we observe a major impact of export activity in the probability to innovate in product that in process. On the other hand, firm size affects much more the decision to innovate in process than in product. Whether there is a recession in the output market, both activities are affected negatively in a same magnitude.

Finally, Table 3 allows us to estimate the coefficient of *EP*, a variable for which we have only information available for 1990. The empirical evidence indicates that firms producing and selling standarised products (*EP* = 1), have a higher probability to innovate in product and a lower probability to innovate in process. Product innovation gives the opportunity to differentiate the product and increase profits, and this increase will probably be relatively higher for firms which have a more standarised product to begin with. The negative coefficient of *EP* in the process innovation equation can be interpreted as that the cost reducing due to process innovations increase relatively profits when the product is not differentiated, and therefore the price elasticity of demand is higher in absolute terms (Kamien & Schwartz, 1970). In that sense, H5 is confirmed.

The assumption that firm specific effects do not matter, is rejected. We confirm this result when comparing the coefficients in Tables 3 and 4. These comparisons should be done amongst the estimates in columns 3 and 5 of Table 3 with respect to those in Table 4. The control of managerial ability and experience in developing innovation activity really affect the influences of explanatory variables on the decisions to innovate, except for firm size and demand growth. Once taking account managerial ability, the experience repercussion on innovation reduces considerably. Anyway, we continue observing innovation as a heterogeneous activity.

Within Table 4, the empirical evidence is in favour of the hypothesis of correlation between firm specific effects and other explanatory variables. Blundell et al. (1995) also found evidence of such correlation. This correlation is different along the determinants of both innovation types. While we observe positive correlation among managerial ability and the regressors related to external markets (DEXP and CAPEXT), this pattern is not maintained with respect to others determinants. We could justify this behaviour since in exporting firms and in those with high foreign capital participation rates the managerial ability is more disciplined by the market. On the other hand, the effect of these variables on the two decisions are different. We observe a larger (lower) impact of export activity (foreign ownership) in product innovation.

Allowing for correlation among firm effects and KSA, more capital intensive firms show higher innovation activity, thus confirming H3. This means that the ability of the manager affects inversely the probability to innovate likely because those firms are more rigid and hierarchical.

As expected and stated in H4, higher vertical integration is associated with higher innovation activity, both in product and in process innovations (the coefficient of *CISP*, purchases over production, is negative). However, while the ability of the manager is positively correlated with firms which are low vertical integrated in the decision of doing product innovation activity, it is negatively correlated with the decision of engaging process innovation activity. Firms with higher vertical integration need a bigger effort of board equipment in doing process innovations.

Among the explanatory variables which capture industry-market effects, we observe a negative coefficient of the industry R&D activity, *SPILL*, on process innovation. This result contrasts with the evidence often detected of a positive relationship between firm and industry R&D expenditures. This positive association has been interpreted as a positive effect of technological opportunities on R&D activity. The negative coefficient of *SPILL* in the probit estimation would be interpreted in terms of negative incentives to innovate, for a given stock of technological capital, due to the increasing facilities to imitate the innovation as the technological opportunities of the market (more intensity of R&D) also increases. This interpretation would also be consistent with the evidence that the absolute value of the coefficient of *SPILL* is larger in process innovations than in product innovations. Consequently, these results reject H1.

We observe that the behaviour of market competition on the decisions to innovate is not monotonic. There exists a threshold of competition (which is estimated to be significantly equal to the mean of AVGMBE) that determines the degree of influence. With high competition, the probability to innovate grows because in the output market there exists opportunities of success in developing innovations, but when market competition achieves the threshold, we observe that the probability to innovate decreases. Again, we detect correlation between managerial ability and market competition. These results compare with Blundell et al. (1995) that found a positive effect of competition on innovation activity and Kraft (1990) that reports an effect of market structure on product innovation but not in process innovation. We fail to reject H6 taking into account the two coefficients.

The effect of size on innovation is always higher for process innovations indicating that large firms have more facilities (internal capabilities, resources) to innovate in process than in product. So, for a given stock of technological capital, size increases are always associated with increases in innovation activities, confirming that larger firms are in a better situation than smaller ones when translating R&D effort into process innovations (H2). This result contrast with the empirical evidence often found on a "U inverted" relationship.[14] On the other hand, firms in recessive product markets innovate less than firms in markets where demand grows or is stable. This evidence is consistent with Schmookler's thesis that innovation is demand-push.

Finally, we are also interested in testing the complementarity (in probability) between innovation measures. We have introduced, as explained in the empirical analysis, predetermined alternative innovation indicator variables in order to test this hypothesis. Process innovation has an important role in the probability to innovate in product as well as product innovation has it in the innovation in process, and the size of those effects are reduced when we have into account the unobserved firm effects. One could consider that the experience in doing innovation as a specific firm effect is positively correlated with the production of innovations in the past. In particular, it is possible that the production of new product inventions could be more affected by the experience than the development of production processes. It would be coherent with Kraft's results, although both the measurement of technical variables and the estimation methods are different. However, Kraft only finds evidence in one direction, i.e. he only shows a positive impact of product-innovation on process-innovation. We provide evidence for the reverse effect: process innovation has positive effect on product innovation which is in line with the simultaneity of both activities.

As a conclusion of this paper we summarise in Table 5, the marginal effects of the explanatory variables on the probability to innovate in product and process, conditional on a given level of a knowledge stock. A change of regime from non-innovating to innovating in process in the last year increases the probability of innovating in product by 27.3%. The experience in product innovations encourages the process innovation probability in 36.3%. Therefore, capital intensive firms and exporters produce major product innovations, given a knowledge stock, but large firms produce major process innovations. A 1% increment in employment level produces only an increment of 1.5% in the probability to innovate in product while a 5.2% in the probability to innovate in process. The effect of competition degree is double in firms doing product innovation with respect those carrying out process innovations, indicating that increases in competition affects more to the production of new products by the threat of imitation On the other hand, the technological opportunity has a negative influence only on process innovation. A demand recession reduces the probability to innovate in similar magnitude in both innovation

TABLE 5
Marginal Effects Conditional on a Given Knowledge Stock[1,2]

	IPROD	*IPROC*
$IPROD_{t-1}$		0.363
$IPROC_{t-1}$	0.273	
KSA_{t-1}	0.002	0.001
$GINST_{t-1}$	0.096	0.000
$SPILL_{t-1}$	0.003	−0.023
$DEXP_{t-1}$	0.063	0.029
$AVGMBE_{t-1}$	0.021	0.011
$AVGME2_{t-1}$	−0.111	−0.052
$lnEMP_{t-1}$	0.015	0.050
$RECES_{t-1}$	−0.025	−0.020
$CAPEXT_{t-1}$	−0.011	−0.034
$CISP_{t-1}$	−0.070	−0.033

Notes.
1. Figures are calculated at sample means.
2. The marginal effects are evaluated as the product of the density function at maximum likelihood estimators and the corresponding estimate. For dummy variables (IPROD, IPROC, DEXP, RECES and CAPEXT), we calculate probabilities at the two regimes and the marginal effect is the increase (decrease) of changing from regime 1 (innovate) to regime 0 (do not innovate).

activities. Finally, we confirm Malerba's hypothesis that higher vertical production control implies higher probability to innovate. Approximately, 1% change in vertical integration increases 7% the probability to innovate in product and 3% that corresponding to process.

Results obtained in this exercise allow us to conclude that Spanish firms do not differ a lot from other industrialised countries when we test hypotheses using the same measures of technological change (Brouwer & Kleinknecht (1998) for Europe and Arundel and Kabla (1998) for Italy, for instance).

The added value of this paper could be summarised in two points. First, we estimate an implicit production function of innovation where the determination of output innovations is function of firm characteristics and market conditions. Moreover, we check that technological activity is not homogeneous so we estimate two equations: one for product innovations and other for process innovations. Second, the availability of having panel data allows us to use estimation methods that overcome possible biases derived from the omission of relevant unobserved firms specific variables among the explanatory variables. On the other hand, we leave for a further research the possibility to extent the study by using other measures of the innovation output.

NOTES

1. Pavitt et al. (1987) found that innovation intensity was greater for large firms and small firms, and smaller for medium-sized, in the UK industry. In contrast, Soete (1979) suggested that R&D intensity increased with size in a number of sectors in the US. Blundell *e*t al. (1993) using the innovation counts found that higher market share firms innovate more, while firms in competitive industries tend to have a greater probability to innovate.

2. NACE is a general industrial classification of economic activities within the European Community and CLIO is the Classification and Nomenclature of Input-Output table. Both classifications are officially recognised by the Accounting Economic System.

3. Innovating firms are those that in the period develop at least one type of innovation: product, process or both simultaneously. Non-innovating firms are those that do not engage in any innovation activity in the period. Innovation is defined according to direct question formulated to the firm in the questionnaire, as "Do you carry out product/process innovations? So, this calls both for radical and incremental innovations although the interviewer should try to control for minimum incremental innovation.

4. See Link (1982), Scherer (1983), Link and Lunn (1984), Lunn (1986) or Kraft (1990).

5. It is possible, for instance, to consider both the influences of the latent and observed product indicator on the decision to innovate in process and vice-versa. In the first case, the interpretation is that not only the output but also the probability matter while in the second, the assumption is that the information of previous periods is perfectly now in the current period.

6. As in other studies, we use a depreciation rate equal to 30%. We normalise by firm sales after obtaining G.

7. Alternatively, we could assume that knowledge stock is obtained using number of patents or number of innovations as in Blundell et al. (1995).

8. It measures the replacement value of the firm's machinery capital stock following the traditional literature about the measurement of capital stock while constructing it (Blundell et al. 1992).

9. A typical variable employed to measure the market structure is the concentration. Cohen and Levin (1989) offer a complete overview of the relationship between R&D and concentration and an extensive discussion about the ambiguous predictions obtained in empirical studies.

10. These authors separate process from product innovation and find opposite results. While in Lunn (1986), concentration is precisely estimated only in the process equation, Kraft (1990) finds that concentration only affects to the product equation.

11. The statistics of the main variables (see Martínez-Ros, 1998) reveals that the two sets of firms are very similar. Two reasons seem to justify this behaviour. First, the data correspond to the same companies or, second, both activities seem to be complements more than substitutes.

12. We consider the lagged observed variable of the alternative equation affects the contemporary decision to innovate. The results of these models are valid under not correlated mixed error terms. We also need absence of correlation between the individual component of the product equation and the lagged process indicator and the individual component of the process equation and the lagged product indicator. These last assumptions are relaxed in the estimation of Table 4.

13. We observe that the coefficients (sign and significance) change when moving from a specification without firm specific effects to a specification considering them.

14. See Pavitt et al. (1987).

REFERENCES

Acs, Z. J., & Audretsch, D. B. (1987). Innovation, market structure and firm size. *The Review of Economics and Statistics*, *71*, 567–574.

Amabile, T. M. (1983), *The social psychology of creativity.* Springer-Verlag, New York.

Arundel A, & Kabla, I. (1998). What percentage of innovations are patented? Empirical estimates for European firms. *Research Policy*, *27*, 127–141.

Arrow, K. J. (1962). Economic welfare and the allocation of resources for invention. In Universities-National Bureau Commitee for Economic Research, *The rate and direction of inventive activity*. Princeton: Princeton University Press.

Blundell, R. W., Bond, S., Deveraux, M., & Schantarelly, F. (1992). Investment and Tobin's Q. *Journal of Econometrics*, *51*, 233–257.

Blundell, R. W., Griffith, R., & Van Reenen, J. (1993). Knowledge Stocks, persistent innovation and market dominance: Evidence from a panel of British manufacturing firms. IFS WP 93/19.

Blundell, R. W., Griffith, R., & Van Reenen, J. (1995). Dynamic count data models of technological innovation. *The Economic Journal*, *105*, 333–344.

Bound, J., Cummins, C., Griliches, Z., Hall, B. H., & Jafee, A. (1984). Who does R&D and who patents? In Z. Griliches (Ed.), *R&D, Patents and Productivity*. Chicago, University of Chicago for the NBER.

Bozeman, B., & Link, A. N. (1983). *Investments in technology: Corporate strategies and public policy alternatives*. New York: Praeger.

Brouwer, E., & Kleinknecht, A. (1998). Innovative output and a firm's propensity to patent. An exploration of CIS micro data. *Delft Economic Papers* 1998-4.

Cohen, W. M., & Levin, R. C. (1989). Empirical studies of innovation and market structure. In R. Schmalensee & R. Willig (Eds.), *Handbook of Industrial Organisation*, Amsterdam, Elsevier.

Crepon B., & Duguet, E. (1997). Research and development, competition and innovation Pseudo-maximum likelihood and simulated maximum likelihood methods applied to count data models with heterogeneity. *Journal of Econometrics 79*, 355–378.

Daft, R. L. (1978). A dual-core model of organizational innovation. *Academy Management Journal*, *21*, 193–210.

Deward, R. D., &. Dutton, J. E. (1986). The adoption of radical and incremental innovations: An empirical analysis. *Management Science*, *32*(11), 1422–1433.

Ettlie, J. E., Bridges, W. P., & O'Keefe, R. D. (1984). Organization strategy and structural differences for radical versus incremental innovation. *Management Science*, *30*(6), 682–695.

García-Montalvo, J. (1993). Patents and R&D at the firm level: a new look. *Revista Española de Economía, Monográfico: Investigación y Desarrollo*, pp. 67–82.

Griliches, Z., & Mairesse, J. (1984). Productivity and R&D at the firm level. In Z. Griliches (Ed.), *R&D, Patents and Productivity*: 339-74. Chicago, University of Chicago Press.

Hall, B. H. (1990). The impact of corporate restructuring on industrial research and development. *Brookings papers on Economic Activity: Microeconomics*, 85–124.

Hall, B. H., & Mairesse, J. (1993). *Exploring the productivity of research and development in French manufacturing firms.* National Bureau of Economic Research and Centre de Reserche en Economie et Statistique. Working Paper 9326.

Hall, B., Griliches, Z., & Hausman, J. (1986). Patents and R&D: Is there a lag? *International Economic Review*, 27.

Kamien, M. I., & Schwartz, N. L. (1970). Market structure, elasticity of demand, and incentive to invent. *Journal of Law and Economics*, *13*, 241–252.

Kamien, M. I., & Schwartz, N. L. (1982). *Market structure and innovation.* Cambridge University Press.

Kraft, K. (1990). Are product- and process-innovations independent of each other? *Applied Economics, 22*, 1029–1038.

Leonard, -Barton, D., & Deschamps, Y. (1988). Managerial influence in the implementation of new technology. *Management Science*, *34*(10), 1252–1265.

Levin, R. C., Cohen, W. M., & Mowery, D. C. (1985). R&D appropiability, opportunity and market structure: New evidence on some Schumpeterian hypotheses. *American Economic Review, Papers and Proceedings*, *75*, 20–24.

Levin, R. C., & Reiss, P. C. (1984). Test of a Schumpeterian model of R&D and market structure. In Z. Griliches (Ed.) *R&D, patents and productivity.* Chicago: University of Chicago Press.

Link, A. N. (1982). An analysis of the composition of R&D spending. *Southern Economic Journal*, *49*, 342–349.

Link, A. N., & Lunn, J. (1984). Rates of return to R&D and market structure. *Review of Industrial Organization*, *1*, Autumn, 232–239.

Lunn, J. (1986). An empirical analysis of process and product patenting: A simultaneous equation framework. *The Journal of Industrial Economics*, *34*, 319–330.

Malerba, F. (1985). *The semiconductor business: The economics of rapid growth and decline.* Madison: University of Wisconsin Press.

Martínez-Ros, E. (1998). *Innovation and rents: Three empirical essays using data from Spanish manufacturing firms.* Doctoral Thesis. Universitat Autónoma de Barcelona. Barcelona.

Moch, M. K., & Morse, E. V. (1977). Size , centralization and organizational adoption of innovations. *American Sociological Review*, *42*, 716–725.

Pavitt, K., Robson, M., & Townsend, J. (1987). The size distribution of innovating firms in the U.K.: 1945-1983. *Journal of Industrial Economics, 35*, 297–316.

Reinganum, J. (1989). The timing of innovation. In Schmalensee & Willig (Ed.) *The Handbook of Industrial Organization* Vol I.

Scherer, F. M. (1983). Concentration, R&D, and productivity change. *Southern Economic Journal*, *50*, 221–225.

Schmookler, J. (1966). *Invention and economic growth.* Cambridge, Mass: Harvard University Press.

Schumpeter, J. A. (1942), *Capitalism, socialism and democracy.* New York, Harper. Scott, J.T. (1984). Firm vs. industry variability in R&D intensity. In Z. Griliches (Ed.) *R& D, Patents and Productivity.* Chicago: University of Chicago Press for the NBER.

Soete, L. L. G. (1979). Firm size and inventive activity: The evidence reconsidered. *European Economic Review*, *12*, 319–340.

Spence, A. M. (1975). Monopoly, quality, and regulation. *Bell Journal of Economics*, 6, 417–29.

Symeonidis, G. (1996). Innovation, firm size and market structure: Schumpeterian hypothesis and some new themes. *OCDE Economic Studies*, *27*, 35–70.

Zmud, R. W. (1984). An examination of "Push-Pull" theory applied to process innovation in knowledge work. *Management Science, 30*, 727–738.