DOCUMENTOS DE TRABAJO

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EXPLAINING THE ADOPTION OF PROCESS TECHNOLOGIES IN SPANISH MANUFACTURING FIRMS

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ABSTRACT

This paper investigates the factors affecting the multiple adoption of new process technologies in manufacturing. We focus our attention on the effect of both financial resources and absorptive capacity as conditioners of the decision to introduce the technology. We argue in favour of a negative effect of financial constraints and provide reasons for a differential effect of internal and external R&D on innovation adoption. Additionally, the methodology allows us to consider the possible complementarities arising when firms adopt several new process technologies. Our results show that financial constraints are dependent on the technology analysed, whereas only internal R&D investments are strong predictors of adoption. We are also able to present evidence that the three technologies analysed (CNC, CAD and robotics) are, to some extent, complementary.

JEL codes: L11, O33

***Keywords**:* Diffusion, adoption, process technologies, absorptive capacity, internal R&D

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1. INTRODUCTION

Since the work of Griliches (1957), the question of why firms adopt new technologies when they do has received increasing attention in the literature. The motivation underlying this interest has been the observation that firms do not adopt them immediately nor fully. Consequently, the main objective of the studies has been to provide the basic feedback for the design of optimal diffusion policies from a public point of view. The literature has proceeded along two parallel lines. A first group of researchers have been interested in the factors influencing the (first) adoption of new technologies by firms (the *inter-firm* diffusion process - see, for example, Mansfield, (1968) or, more recently, Astebro, 2002). In contrast, a second group has centered its efforts on the analysis of the intensity with which firms make use of the new technology (so called *intra-firm* diffusion - see, for example, Fuentelsaz, Gómez and Polo, 2003 or Astebro, 2004).

Despite the interest in these two areas, the diffusion of innovations has historically lacked the importance of other stages in the process of technological change from a public policy point of view (Stoneman and Diederen, 1994), which has limited the discussion of diffusion policy in the literature (Stoneman, 2001). This is surprising, given that it is through their diffusion that the products of invention and innovation are widely available to users and produce their economic benefits. The adoption of new process technologies has been shown to have positive effects on firm performance (Stoneman and Kwon, 1995). In addition, the international evidence suggests that technological diffusion influences the pace at which countries converge in terms of productivity (Franztsen, 2004).

Our objective in this paper is to analyze the adoption of new technologies at the firm level (*inter-firm diffusion*). In doing so, our intention is to contribute to the literature in three ways. First, by adding new evidence, we expect to collaborate in reducing the difference, in terms of the amount of attention paid by researchers, between the two first stages of the process of technological change (invention and innovation) and the third, the diffusion of the resulting technologies. At the same time we also attempt to narrow the gap detected between theoretical developments and empirical research on the literature on diffusion (Karshenas and Stoneman, 1993).

Second, our research focuses the attention on the effect of firm's financial structure and absorptive capacity on technology adoption. In the case of the former, it is an empirical regularity that larger firms are more likely to introduce new technologies. Nevertheless, as Astebro (2002) has shown, this result could be due to other reasons associated with size. Apart from these reasons, firm size could also be related to the capacity of firms to collect funds to finance investments in new technologies. In fact, financial constraints have been proposed as determinants of both inter (Canepa and Stoneman, 2005) and intra-firm diffusion processes (Fuentelsaz, Gómez and Polo, 2003) and we attempt to disentangle both effects in our empirical analysis. In addition, the concept of absorptive capacity, usually understood as a byproduct of R&D investments (Romeo, 1975, 1977; Karshenas and Stoneman, 1993), has been frequently used as an additional element justifying differences in adoption behavior among firms,. Unfortunately, to our knowledge, research has not attempted to distinguish between the possibly differential impact of internal and external knowledge acquisition activities on adoption. Although research on complementarities in innovation strategy has analyzed this issue, it is absent from the literature on adoption. In particular, we provide arguments leading to the conclusion that internal R&D investments should have a higher impact on the probability adoption than external ones.

Finally, we pay attention to the interrelations in the adoption of multiple technologies. As Stoneman and Kwon (1994) have pointed out, most of the literature on technology diffusion has been concerned with individual technologies. However, "technologies may be complements or substitutes in the production process" (Stoneman and Kwon, 1994: 420). This can create a critical problem when estimating models of adoption. However, recent methodological developments on multivariate probit models that allow the joint estimation of the adoption equations for different technologies (Capellari and Jenkins, 2003) will allow us to control for the possible bias.

With all these arguments in mind, we explore the determinants of the adoption of three new process technologies in Spanish manufacturing: computer numerically controlled machines (CNC), computer aided design (CAD) and robotics. These have been the subject of prior attention in the literature (see, for example, Astebro, 2004, Stoneman and Battisti, 2005 or Swamidass, 2003). The availability of information related to these three technologies allows us to analyze the possible interdependences arising in the process (Stoneman and Kwon, 1994). An important feature of our data is that they have a longitudinal dimension: the information on the adoption behaviour of firms was collected through a series of surveys carried out in 1994, 1998 and 2002. A multivariate probit model, which is estimated by simulated maximum likelihood techniques, is used to test our hypothesis. There are some appreciable advantages in using this model. In particular, we are able to control more effectively for unobserved heterogeneity across firms. Furthermore, testing for the presence of complementarities between the three technologies is quite direct using this model.

The rest of the paper is structured as follows. Section 2 develops the hypothesis to be tested in the paper. In Section 3 we describe the characteristics of the sample and the methods used in the estimations. Section 4 presents the results. Finally, Section 5 discusses the main conclusions and implications derived from the analysis.

2. LITERATURE REVIEW AND HYPOTHESES

The inter-firm diffusion of new technologies proceeds as each firm takes the decision to invest into a new technology. The literature has contended that this investment is motivated by four main types of factors: rank, stock, order and epidemic effects (Karshenas and Stoneman, 1993). The existence of rank effects is based on the assumption that firms are different in terms of the relevant characteristics that determine the profitability of using an innovation. Stock and order effects refer to the number of competitors adopting the new technology and the position of the firm in the order of adoption. On the one hand, the marginal profitability to an adopter diminishes as the number of competitors using the new technology rises (stock effect). On the other, early adopters obtain higher returns from the adoption of new technology (order effects). Finally, the epidemic effect captures the idea that the decision to adopt depends on the amount of information available on the existence and profitability of a new innovation, which increases as the number of users of the new technology grows.

Recent research on the diffusion of innovations has added three additional elements to the analysis of the decision to adopt a new technology. First, some authors have investigated alternative explanations for the effect of firm size. For example, Astebro (2002) explores the influence of four variables related to corresponding alternative explanations: noncapital investment costs, equipment replacement, risk aversion and learning. Firm size has also been a variable frequently related to the availability of financial resources in a context in which financial markets are imperfect (Fuentelsaz, Gómez and Polo, 2003). Large firms are argued to have important internal capital markets that may be used to finance investments in new technologies and big, diversified firms may also be perceived by financers as less risky.

The influence of financial constraints on the diffusion of new technologies has been a theme recently introduced in the literature. Although it is widely accepted that the availability of funds conditions investment decisions, its effect over particular innovations has not been extensively studied (Stoneman, 2001). While the introduction of some innovations may not require large investments, others demand not only a considerable amount of capital, but, also, changes in production processes or noncapital investments which need additional funds.

Second, with the advent of the resource-based view of strategy (Wernerfelt, 1984; Barney, 1991) some papers have refined the idea of a pure epidemic effect by relating the amount of information available on a new technology to a firm's capability to interpret and respond to it. Though less used in an adoption of innovations context, the literature has paid special attention to the concept of absorptive capacity (Cohen and Levinthal, 1990) in order to refer to the ability of firms to acquire, understand, value, assimilate and exploit the information available in the environment. Subsequently, other authors (e.g., Zahra and George, 2002) reconceptualize the idea of absorptive capacity introduced by Cohen and Levinthal (1990). Although researchers have generally tended to associate this concept with R&D expenditures, the definitions offered in these papers and the general framework of the resource-based view illustrate the difficulties associated with the identification of these factors in practical terms.

A third feature of recent research is the consideration of interdependencies among technologies when explaining the decision to adopt. The traditional analysis of diffusion has studied the introduction of one technology in isolation from other technologies (Stoneman and Kwon, 1994). Nevertheless, technologies may be complements or substitutes and the decision to adopt one type may either increase or reduce the probability of introducing another. For example, Stoneman and Kwon (1994) find that the introduction of numerically controlled machine tools affects (and is affected by) the adoption of coated carbide tools. However, the fact that the implementation of new technologies may be influenced by managers and end-users (Leonard-Barton and Deschamps, 1988) or, as suggested by the absorptive capacity concept, by the existence of adequate channels for information exchange within the firm, widens the array of firm-specific variables explaining adoption. Thus, an alternative explanation to the complementary hypothesis could be that the multiple adoption of new technologies could be explained by an intrinsic propensity of firms to adopt them. Just as more fragile individuals would tend to adopt healthier behaviours but would also present higher mortality rates, firms more capable to understand, assimilate and exploit new technologies would show a higher likelihood of multiple adoption, even if the technologies are not interrelated. Although it is important to recognise the difficulties associated with distinguishing between firm- and technology-associated explanations (or a combination of both) for multiple adoption, there should be a real concern with controlling for these effects in order to avoid bias in the estimations.

In this paper we take these considerations into account when designing and measuring our hypotheses and when developing our estimations. As mentioned in the introduction, we place special emphasis on the importance of firm-specific characteristics that influence the decision to use a new technology. We attempt to distinguish between size and financial structure effects and consider the absorptive capacity concept, taking into account both its internal and external sources. We delay the treatment of the methodological problems associated with the estimation of multiple adoption until Section 3.

Firm size and financial structure. The reasons offered in the literature to justify a positive effect of firm size on the decision to adopt a new technology are multiple. Larger firms are able to spread the cost of investing in a new technology among a higher number of units (Cohen and Levin, 1989) or they are more likely to possess the specialised complementary assets needed for the commercial success of innovations (Teece, 1986). Romeo (1975) maintains that larger firms are generally expected to have higher incentives to use new technologies for three reasons. First, they tend to have more equipment in use than smaller firms and, consequently, they are expected to have more equipment in need of replacement. Second, the wider range of operations in which they are involved makes it more likely that they perform activities suitable for the use of a new technology. Finally, larger firms have more resources available to them and are more likely to be able to finance an investment and to absorb a loss should a risky investment occur.

The empirical evidence tends to favour the positive effect of size on inter-firm diffusion. This positive influence is consistent across different sectors and technologies and examples are found in the electric utility industry (Rose and Joskow, 1990), in the engineering and metalworking industries (Baptista, 2000, Swamidass, 2003) and the banking industry (Hannan and Mc Dowell, 1984a,b,1986; Sharma, 1993, Buzzachi, Colombo and Mariotti (1995).

Hypothesis 1: *firm size is expected to have a positive effect on the decision to adopt new technologies*

Romeo (1975)'s third reason focuses on the existence of capital market imperfections in order to justify the positive effect. Larger firms may be more able to collect the internal or external funds to finance the investment associated with the acquisition of a new technology. Despite the foreseeable significance of this variable for explaining diffusion, only a few papers pay adequate attention to it, separating the effect of firm size from financial constraints. For example, Canepa and Stoneman (2005), in an inter-firm diffusion context, consider the effect of cash flow on the decision to adopt computerised numerically controlled machine tools. Similarly, Fuentelsaz, Gómez and Polo (2003) assess the impact of firm profitability and total reserves in the intra-firm diffusion process of automated teller machines.

Although it is an aspect that is frequently neglected in the analysis of diffusion, in these papers, the availability of funds tends to turn out to be a key factor for explaining it. The introduction of an innovation may require significant investments in order to acquire the units needed for production. In the case of process innovations, the costs associated with restructuring the production process and the costs of learning how to use the innovation effectively may impose additional charges on adoption. At least three reasons may explain the difficulties of some firms to raise funds to finance these investments (Stoneman, 2001): uncertainty, information asymmetries and firm-specific assets. Adoption investments are likely to be surrounded by uncertainty about the cash flows to be perceived, which may create difficulties for raising funds externally. This difficulty in valuing the returns on an adoption project is exacerbated by the fact that the potential financers are worse informed than the users or suppliers of the innovation. Finally, funds may be partially invested on the acquisition of intangibles (e.g., learning) with a low value in the market. In this context and, aside from size effects, firms with extensive internal financial sources may find adoption easier (Stoneman, 2001).

Hypothesis 2: *for a given firm size, the internal availability of funds is expected to have a positive effect on the decision to adopt new technologies*

Absorptive capacity, defined by Cohen and Levinthal (1990, p.1) as the “ability of a firm to recognize the value of new, external information, assimilate it and apply it to commercial ends” may be a critical factor in enhancing a firm’s likelihood to adopt and its capacity to use new and complex technologies. In the context of technology diffusion, the concept suggests a refinement of the assumptions underlying pure diffusion models. These models relate the diffusion of an innovation to the level of available information on the new technology. Therefore, the mere exposition to information on a new technology would explain diffusion. As information spreads through an epidemic-like process, diffusion proceeds, depicting the traditional S-shaped curve.

The advance introduced by the concept of absorptive capacity is to relate diffusion not only to the level of information available in the environment, but also to the capacity of the firm to understand and exploit it for commercial ends. Paraphrasing the literature (Cohen and Levinthal, 1990; Lane, Koka and Pathak, 2006: 856), the ability of a firm to use the external knowledge embodied in innovations would follow three sequential processes. First, it would be necessary to recognize and understand potentially valuable new technologies (exploratory learning). Second, the new technology should be related to the internal body of knowledge being used inside the firm and to the processes taking place in it (transformative learning). Finally, this knowledge should be applied (exploitative learning). Therefore, with complex technologies, the mere contact assumed by diffusion models would not be enough to explain introduction. Moreover, relating innovation-embodied knowledge to internal processes and exploiting it would require not only the existence of adequate external channels of communication, but also an adequately structured organization (Cohen and Levinthal, 1990).

The literature has usually conceived absorptive capacity as an increasing function of firm investments in R&D. This relation stems from Cohen and Levinthal’s (1989) seminal paper, in which absorptive capacity is seen as a byproduct of firm R&D investments. Therefore, R&D-intensive firms should be quicker to adopt new technology because they would be more likely to be able to understand it. In addition, firms investing in R&D would be more aware of changes and this, in turn, should create pressures for change, increasing the proclivity to adopt new techniques (Srinivasan, Lilien and Rangaswamy, 2002; Zahra and George, 2002). Finally, firms undertaking research and development would be able to reduce the risks associated with the adoption of a new technology (Von Hippel, 1988; Cohen and Levinthal, 1990).

Hypothesis 3: *a higher absorptive capacity is expected to have a positive effect on the decision to adopt new technologies*

Although the literature on diffusion has made use of the absorptive capacity concept, it has not debated the differential effect that the various types of R&D activities could have on technology adoption. Nevertheless, in principle, the absorptive capacity of a firm could be generated from both internal and external sources, which would suggest a distinction between absorptive capacity as a byproduct of in-house or as a result of external R&D investments. The effect of each type of investment on the capacity of firms to understand information on new technologies should be different for reasons related, at least, to (1) the processes of learning and (2) the attributes of knowledge.

It is widely documented that learning occurs as an associative process in which new knowledge is incorporated cumulatively as a link is established with pre-existing concepts (Cohen and Levinthal, 1989, 1990). When a new technology is available in the market, the firm requires both a comprehension of the specific processes and activities that take place inside the firm and the characteristics of the technology in order to be able to understand and assess its benefits (i.e., to undertake exploratory and transformative learning). That is, firms must effectively combine the two different types of information (firm- and technology-specific) to assess the decision to adopt. Knowledge generated from internal activities is expected to better combine these two different types of information, given that an understanding of technology and firm routines and processes is expected to be integrated in them.

Although one could argue that external knowledge generating activities (external R&D investments) also require an integration of both types of information, the degree to which this is achieved should be lower, given the characteristics of the information to be shared. On the one hand, the results of externally developed knowledge acquisition activities may be difficult to transmit to decision makers inside the firm as a consequence of tacitness, which makes it difficult to decode and transmit this knowledge inside the firm. On the other, according to Cohen and Levinthal (1989, 1990) for the knowledge from external activities to be effectively integrated inside the firm, there has to be an effort to achieve it. That is, mere exposure of decision makers to the result of external activities should produce a lower enhancement of absorptive capacity than the development of internal activities.

Hypothesis 4: *the effect of internally generated absorptive capacity on the decision to adopt new technologies should be more important than the effect of the one externally originated*

3. SAMPLE DESCRIPTION

A basic problem in estimating diffusion models has always been the availability of data. As mentioned in the introduction, the data available for the analysis refer to the diffusion of three process innovations: numerically controlled machines (CNC), computer aided design (CAD) and robotics. Although these technologies have been the subject of close attention (see, for example, Karshenas and Stoneman, 1993 or, more recently, Astebro, 2004), the evidence is mainly restricted to the UK and the US (but see Colombo and Mosconi, 1995). The use of all the three technologies has been reported to be appropriate for manufacturing industries, in which we focus our empirical analysis. More precisely, they all contribute to the automation of production through the building of flexible systems that combine these, and possibly, other elements of production (for example, local area networks) in complex and varied forms. Previous research on these technologies (Milgrom and Roberts, 1990; Colombo and Mosconi, 1995) has argued that they are, in effect, complementary. In particular, Milgrom and Roberts (1990: 514) maintain that “CAD equipment and flexible manufacturing technologies, shorter production runs, lower inventories, increased data communications, and more frequent product redesigns are complementary”.

The dataset used for this study is drawn from the Survey of Business Strategies (ESEE) an annual survey compiled by the Spanish Ministry of Industry since 1990. Different parts of this data set have been previously used in the analysis of diversification decisions (Merino and Rodríguez, 1997), the effect of R&D on productivity (Beneito, 2001) and the introduction of product and process innovations (Martínez Ros, 2000) in the Spanish economy. The survey covers a wide range of firms with 10 or more employees and is an attempt to characterize the firms in the Spanish manufacturing sector. Therefore, one of the important attributes of this sample is that it is representative of the manufacturing firms operating in the Spanish economy. The sample covers the population of Spanish manufacturing firms with 200 or more employees. Firms with at least 10 employees but less than 200 employees were selected by a random sampling scheme in the initial year. In subsequent years firms that drop out of the original sample are replaced every year by firms with similar characteristics according to the sampling procedure used in the base year. Therefore, the data set reproduces the entry and exit process that takes place in the population.

Although the survey has been administered annually to firms since 1990, questions related to adoption behaviour are only included in the questionnaire every four years. This means that the questionnaire provides us with information that refers to years 1994, 1998 and 2002. Two points concerning the data should be noted. First, the innovations included in the survey are not specific to a particular industry and can be used in a wide range of manufacturing settings, although we might expect that some technologies are more likely to be adopted in certain activities. Second, we know whether a plant uses or not a specific technology; nevertheless we do not know the intensity of usage or the date of adoption.[1] However, our dataset also has some advantages. On the one hand, it refers to a panel of manufacturing firms that are representative of the Spanish industrial sector. On the other, it provides us with information on a set of firm characteristics, what allows us to test for the ones which foster adoption. The selection of the sample and the rejection of cases with missing data in the basic variables results in an incomplete panel of 2,396 firms and 4,590 observations that will be used in the analysis[2].

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[1] This precludes us from using survival analysis techniques, given that we would need information on the date of adoption of each technology by the firm in order to identify the time in which the event (adoption in our case) takes place.

[2] The sampling procedures implemented to collect the data make sure that the sample of firms is representative of the total population of firms operating in Spain in a given year.

Table 1 offers a first approximation to the data, showing the distribution of adopters and non adopters by technology, firm size and year. Given the different sampling procedures used to select firms depending on their size, we have chosen to perform the descriptive analysis by splitting the sample into the group of firms with less than or equal to 200 employees and those with more than 200 employees. The first regularity observed in the data is that the number of adopters is different depending on the technology. Looking at the 2002 figures, we may conclude that CNC is the technology most used in Spanish manufacturing, given that almost half of the firms in our sample are using it. Computer aided design is used by approximately 37% of the companies, whereas 28% of the firms have introduced robotics into their production process. A second feature of the data is that the introduction of the new technologies seems to be conditioned by firm size. For all the three technologies and the 3 years included in the sample, the group of firms with more than 200 employees presents a higher percentage of adopters than their smaller counterparts. Finally, it may also be observed that the number of adopters grows steadily from 1994 to 2002 for all the three technologies.

Table 1. Number of adopters and non adopters by technology, firm size and year

	CNC						ROBÓTICS						CAD					
	Total		Firm size < 200 employees		Firm size >= 200 employees		Total		Firm size < 200 employees		Firm size >= 200 employees		Total		Firm size < 200 employees		Firm size >= 200 employees	
	Yes	No	Yes	No	Yes	No	Yes	No	Yes	No	Yes	No	Yes	No	Yes	No	Yes	No
1994	510	955	265	724	245	231	275	1190	97	892	178	298	394	1071	182	807	212	264
1998	696	883	420	722	276	161	389	1190	168	974	221	216	551	1028	307	835	193	244
2002	758	788	456	626	302	160	429	1117	187	897	242	220	579	967	333	751	246	216

The expressions "Yes" and "No" indicate whether the firms have adopted or not.

Table 2 presents the sectorial breakdown of the sample. In general terms, numerically controlled machines are adopted by 49.03%, CAD by 37.45 and robotics by 27.75% of the firms in 2002. The sample shows that the behaviour of firms is somewhat different depending on the industry to which they belong and this differences are statistically significant. The motor and auto industry presents an active adoption behaviour in the adoption of all the three technologies. In contrast, leather and footwear is the industry that show the least active behaviour when adopting CAD, numerically controlled machines and robotics.

Table 2. Percentage of adopters and non adopters in 2002 by technology and industry

Industry	Numerically controlled machines Yes	Numerically controlled machines No	Robotics Yes	Robotics No	CAD Yes	CAD No
Meat products	13	27	5	35	3	37
Food and tobacco	46	98	35	109	14	130
Beverages	12	12	16	8	5	19
Textiles and clothing	50	101	19	132	61	90
Leather and footwear	8	38	4	42	3	43
Wood industry	27	28	8	47	11	44
Paper	24	29	10	43	17	36
Edition and graphical arts	43	47	15	75	36	54
Chemical products	39	56	28	67	20	75
Plastic and rubber	52	42	28	66	30	64
Non-metallic minerals	57	50	38	69	31	76
Metallurgy	23	32	17	38	19	36
Metallic products	108	70	59	119	90	88
Machinery for agriculture and industry	76	36	35	77	83	29
Machinery for offices, data processing, etc.	7	10	2	15	7	10
Electrical material and accessories	44	32	33	43	49	27
Motors and autos	54	20	39	35	42	32
Other transport material	20	8	12	16	23	5
Furniture	46	31	21	56	26	51
Other manufactures	9	21	5	25	9	21
Total manufacturing	758	788	429	1117	579	967
χ^2	356.51***		330.41***		822.20***	

3.1 Measurements and Control Variables

To test the predictions of the hypotheses related to firm characteristics, we use the following variables. Firm size (Hypothesis 1) is measured through the number of employees working for the firm in a given year. To proxy for the availability of funds to invest in new technologies, we use the ratio of total debts to assets. A negative sign of the associated coefficient would offer support for Hypothesis 2. The capacity of the firm to absorb new technologies (Hypothesis 3 and 4) is measured through the intensity of research and development spending. In agreement with our arguments, we follow two steps when measuring Hypothesis 3 and 4. First, as the literature usually does, we use the ratio of total R&D spending to total sales, in order to avoid multicolinearity problems. As mentioned before the relationship between R&D and new technology adoption has been empirically tested before. Romeo (1975, 1977) found that R&D has a positive effect on the rate of diffusion of an innovation, even if the innovation is not directly related to the areas in which the R&D is done. Pennings and Harianto (1992) show that the adoption of new technologies is fastest among firms who have previous experience with other technologies. Finally, Karshenas and Stoneman (1993) did not obtain a significant effect of R&D on the speed of adoption. In accordance with Hypothesis 3, a positive sign of R&D spending intensity is expected.

Second, in order to measure the different effects of internal and external R&D spending on the probability of adoption, we build two additional measures: in-house R&D intensity and external R&D intensity. As we would expect the relevance of in-house R&D to be higher, the coefficient accompanying this variable should be positive and higher in magnitude than that of external R&D. Alternatively, a positive and significant coefficient of in-house R&D *and* a non-significant coefficient for external R&D would also offer support for our hypotheses.

Our estimations also introduce a number of controls in order to take into account the effect of other variables affecting the decision to adopt new technologies. We start by referring to firm and market characteristics, and then move on to epidemic effects. With respect to firm characteristics, on the one hand, the literature agrees on the importance of firms' international activities for explaining the proclivity of firms to innovate. The basic argument is that export-oriented firms need innovations in order to cope with the more competitive international markets. In fact, a positive association between export intensity and R&D is found in several papers (Cassiman and Veugelers, 1999; González et al., 1999, and Beneito, 2003). However, the available evidence in a context of technology adoption does not offer conclusive results. Cohen (1975) and Riedel (1975) analyse the relationship between the adoption of new technologies and the export performance of electronic firms in developing countries, finding that firms that used advanced technologies also exported more. However, more recently, Lal (1999, 2002) found that export intensity did not affect the adoption of information technologies. The analysis that is performed in the following section includes the ratio of total exports to sales in order to capture the effect of this variable.

On the other hand, both the presence of foreign investors in the capital of the firm and its corporate status could be affecting the adoption decision. The effect of these two variables on the introduction of the three technologies is not clear. In the case of the former, foreign investments could mean a new channel of information on innovations used elsewhere. This variable has been used to explain product and process innovations (Martinez-Ros, 2000). By corporate status we are referring to the firm being a part of a larger business group. Although information on new technologies could be greater in a corporate group, independent firms could also be quicker at taking the decision to adopt (Bartoloni and Baussola, 2001). We use two dummies to proxy for ownership structure. The first one indicates whether the presence of foreign capital in the focal firm is higher than 30%[3]. The second takes a value of “one” in those cases in which the firm is part of a larger corporate unit.

The effect of market structure on innovation has been one of the most debated relationships among researchers. Following the Schumpeterian hypothesis (Schumpeter, 1970), the possession of some monopoly power should create incentives for firms to adopt the innovation. Firms competing in more concentrated markets would have the opportunity to better appropriate the returns on their investments in new technologies, charging higher prices to consumers. On the contrary, a more competitive market would undermine the capacity of firms for capturing consumer value, slowing the pace at which firms make first use of the technology.

This "monopoly power" view has been contradicted by proponents of the "competitive" hypothesis, who argue that concentration should be detrimental to technology diffusion. Thus,

[3] This is the cut off point used by other empirical studies on industrial settings (Merino and Salas , 1995, 1996).

for example, Quirmbach (1986) maintains that the speed of adoption should be higher in industries experiencing a lower degree of collusion, an outcome more probable in less concentrated markets. Therefore, the arguments offered focus on two conflicting intuitions (Reinganum, 1981). On the one hand, competition provides an incentive to adopt cost-reducing innovations. On the other, the capacity of firms to appropriate the rents derived from the implementation of new technologies grows with concentration.

The empirical evidence tends to show that the number of competing firms will be positively related and the variance of the size distribution inversely related to the rates of diffusion. In other words, in less concentrated industries, the innovation would tend to spread more rapidly than in more concentrated ones (Mansfield 1961, 1968; Mansfield, Rapoport, Schenee, Hamburger, 1971; Romeo, 1975, 1977; Stoneman and Diederen, 1994; Levin, Levin and Meisel, 1987). In our analysis, market structure is captured through the use of a concentration ratio. For each manufacturing sector in the sample, we add up the market share of the four largest firms (CR_4) to build our measure of concentration. A negative sign of this coefficient is expected.

In addition to the inclusion of concentration ratios, other sector-related characteristics could condition adoption decisions. On the one hand, industries differ in terms of the type of activities performed and, therefore, the need to use a given technology. On the other, both the degree of appropriability and the extent to which the sector offers technological opportunities may condition adoption behaviour. Accordingly, we introduce 19 dummy variables to account for the 20 different sectors defined in the survey.

Finally, early work on the diffusion of new technology tended to concentrate upon epidemic theories. In its simplest form, this approach is based on the ideas that (1) a potential user would adopt the technology upon learning of its existence and (2) information on the existence of the technology spreads by direct contact between potential and current users

(Baptista, 1999: 109). This simple combination of hypotheses creates the characteristic path of diffusion over time that results in an S-shaped form. The work of Mansfield (1961) reported statistical confirmation of the general S-shaped form of diffusion curves in a model generating a symmetrical logistic diffusion curve by treating diffusion as a funcion of the accumulated proportion of adopters. According to Mansfield (1968) the number of non-users adopting in a period should increase as the proportion of users in the industry population increases. Therefore, the epidemic effect is measured through the proportion of adopters in the industry to which the firm belongs. A positive sign of the associated coefficient would offer support for the prevalence of epidemic effects. Additionally, we introduce time dummies that should also capture the evolution of information. Specifically, we define two dummies taking a value of "one" for the years 1998 and 2002, respectively.

Table 3 shows a first assessment of the hypotheses developed above. It presents mean values and standard deviations for the variables defined in this section for the different technologies considered and distinguishing between firms which have adopted the new technology and those who have decided not to do so yet. As we predicted, firm size, the intensity of R&D investments and the export behaviour are significant for explaining the different behaviour followed by the firms included in the sample, being positively associated to having introduced the technology. This result is consistent across technologies. Nevertheless, this pattern is not observed in the case of the two other variables, concentration and the availability of funds. Whereas the first is not significant for any of the technologies analysed, the second is only relevant in the case of robotics. This result could suggest that the relevance of this last variable depends on the type of technology under observation.

Table 3. Explanatory variables and the adoption of CNC, robotics and CAD in Spanish manufacturing

	Numerically controlled machines					Robotics					CAD				
	No 2626		Yes 1964			No 3497		Yes 1093			No 3066		Yes 1524		
	Mean		SD		t (p-value)	Mean		SD		t (p-value)	Mean		SD		t (p-value)
	No	Yes	No	Yes		No	Yes	No	Yes		No	Yes	No	Yes	
Firm size	146.37	309.04	352.06	743.60	8.97***	136.30	470.91	298.53	973.88	-11.20***	151.91	344.86	351.15	820.24	-8.79***
Ratio total debts / assets	0.58	0.57	0.24	0.22	0.72	0.59	0.54	0.24	0.21	5.64***	0.57	0.58	0.24	0.22	-1.22
Ratio firm R&D / sales	0.01	0.01	0.02	0.02	-6.07***	0.01	0.01	0.02	0.02	-7.50***	0.00	0.01	0.02	0.02	-10.27***
Ratio in-house R&D / sales	0.00	0.01	0.01	0.02	-5.65***	0.00	0.01	0.01	0.02	-6.64***	0.00	0.01	0.01	0.02	-10.33***
Ratio external R&D / sales	0.00	0.00	0.01	0.01	-3.81***	0.00	0.00	0.01	0.01	-4.90***	0.00	0.00	0.01	0.01	-4.81***
Ratio Export sales / total sales	0.14	0.23	0.23	0.27	-11.73***	0.15	0.29	0.24	0.27	-15.33***	0.14	0.26	0.24	0.27	-14.20***
Concentration ratio(CR_4)	40.61	40.45	13.05	13.88	0.39	40.58	40.42	13.26	13.87	0.33	40.76	40.09	13.03	14.13	1.61

		Numerically controlled machines			Robotics			CAD		
		No	Yes	χ^2	No	Yes	χ^2	No	Yes	χ^2
Integrated in a business group	No	1969	1131	155.07***	2632	468	399.87***	2255	845	152.16**
	Yes	657	833		865	625		811	679	
Foreign capital	No	2257	1476	86.24**	3025	708	258.87***	2612	1121	90.77**
	Yes	369	488		472	385		454	403	

*, **, *** coefficient statistically significant at a 90%, 95% or 99% level.

4. METHODOLOGY AND ESTIMATION STRATEGY

Given our empirical setting, to model the adoption of new process technologies, it seems natural to recur to logit and/or probit type models, in which the dependent variable takes values of "one" or "zero" depending on whether the innovation has been adopted or not. However, our discussion above suggests that the estimation of such a model should be conditioned by both the probable existence of non-observable firm-specific variables and the fact that we consider several technologies. Although both problems may look different, similar solutions may be provided.

In the first case, it is now widely acknowledged that firm decisions are greatly influenced by difficult-to-observe firm-specific effects (Godfrey and Hill, 1995). For example, unobservables have been shown to influence diversification decisions (Merino and Rodriguez, 1997) or entries into new geographical markets (Fuentelsaz and Gómez, 2006). This has generated a critical problem in terms of empirical design, which has been frequently solved through the use of fixed or random effects models. In the second case, although a firm's adoption of several new technologies could be explained by complementarities between them, paraphrasing studies in innovation complimentarity (Miravete and Pernias, 2004), the impact of external shocks or firm-specific characteristics could also be plausible reasons. Without discarding other explanations, the advent of the resource-based view and the introduction of concepts (such as that of absorptive capacity reviewed above) into the diffusion literature suggest that firm-specific factors could also contribute to explaining the observation that some technologies tend to be simultaneously used by some firms. That is, the observed correlation between the use of some technologies could be due to complementarities between them or a consequence of other firm-specific factors that increase the probability of multiple adoption, such as better internal channels for sharing knowledge. The econometric literature has, by now, developed models that are able to capture both situations.

This discussion suggests a natural way to proceed with the empirical analysis. Our departure point is to apply a standard discrete choice model to the adoption decision. Let t represent the decision to adopt a new technology, where t = 0 means that the firm has not adopted and t = 1 means that the firm has introduced the innovation. Similarly, let X represent the vector of independent characteristics and β the one including the coefficients to estimate. If we impose a simple linear form for the adoption, and assume that the error term (ε_i) has a cumulative logistic distribution, this yields the standard logit model:

$$t_i = \beta X_i + \varepsilon_i$$

As mentioned above, despite our careful consideration of the determinants of the decision to adopt new technologies, we have reasons to suspect that our model could be misspecified. In other words, unobserved firm-specific characteristics could be influencing the decision to adopt. In that case, the simple pooled regression could be seriously biased. To avoid this problem, the error term can be thought of as comprising two components, $\varepsilon_{i,j} = \mu_i + \eta_{i,j}$, one of which is a permanent firm-specific effect, μ_i, and the other a transitory effect that picks up exogenous shocks, $\eta_{i,j}$. Furthermore, if we assume that the μ_i's are independently and identically distributed draws from a common distribution and the $\eta_{i,j}$'s are independently and identically distributed with a logistic cumulative distribution, we obtain the random effects logit model that is estimated in the second step.

Lastly, to consider the interdependence effects between different process technologies, we will use a multivariate probit model. The model consists of a recursive system of equations, one for each technology (CNC, Robotics and CAD). Its most important feature is that the random components of each equation are allowed to be freely correlated with the random components of the others. The advantage of this model is that it takes into account the possible existence of unobservable individual characteristics simultaneously influencing the adoption of all three technologies. In other words, the model is able to show whether we are omitting the impact of some variables simultaneously affecting the decision to introduce them.

The estimation is carried out using Stata's mvprobit command which applies the method of simulated maximum likelihood (SML) and uses the Geweke-Hajivassiliour-Keane (GHK) smooth recursive conditioning simulator to evaluate the multivariate normal distribution. Cappellari and Jenkins (2003) state that the simulated probabilities are unbiased and bound within the (0, 1) interval. The variance-covariance matrix, *V*, of the cross-equation error terms has values of 1 on the diagonal, whereas off-diagonal elements (correlations $\rho_{jk}=\rho_{kj}$) have to be estimated (Cappellari and Jenkins (2003)). Here, the parameter ρ_{jk} is the covariance between the error terms of equations *j* and *k*. It measures the extent to which the unobserved factors simultaneously influence CNC, Robotics and CAD adoption.

5. RESULTS

Table 4 shows the estimation of a logit model on the 4,590 observations available. Columns 1, 5 and 9 present a simple model in which only two of the control variables discussed above (time and sector dummies) are introduced. Column 2 (6, 10) tests our first three hypotheses and introduces the control variables. Finally, Columns 3 and 4 (7 and 8; 11 and 12) present two different versions of the full models.

Table 4. A logit analysis of the adoption of CNC, robotics and CAD in Spanish manufacturing (pooled data)

	CNC (1)	CNC (2)	CNC (3)	CNC (4)	Robotics (5)	Robotics (6)	Robotics (7)	Robotics (8)	CAD (9)	CAD (10)	CAD (11)	CAD (12)
Firm size	---	0.60***	0.60***	0.59***	---	1.186***	1.19***	1.19***	---	0.76***	0.76***	0.75***
		(5.39)	(5.39)	(5.25)		(9.26)	(9.26)	(9.25)		(6.10)	(6.09)	(6.01)
Firm debt ratio	---	-0.09	-0.09	-0.09	---	-0.58***	-0.59***	-0.60***	---	0.08	0.08	0.09
		(-0.64)	(-0.64)	(-0.67)		(-3.40)	(-3.40)	(-3.46)		(0.47)	(0.48)	(0.57)
R&D intensity	---	4.52**	---	---	---	5.841***	---	---	---	12.55***	---	---
		(2.47)				(3.00)				(5.87)		
R&D intensity (internal)	---	---	5.21**	5.02**	---	---	6.83***	6.83***	---	---	16.38***	16.12***
			(2.18)	(2.11)			(2.73)	(2.72)			(5.59)	(5.50)
R&D intensity (external)	---	---	2.79	-3.08	---	---	3.22	2.92	---	---	3.62	3.81
			(0.66)	(-0.72)			(0.69)	(0.63)			(0.75)	(0.78)
Market concentration	---	-0.00	-0.03	-0.00	---	-0.002	-0.00	-0.00	---	0.01*	0.01*	0.00
		(-0.48)	(-0.48)	(-0.13)		(-0.43)	(-0.44)	(-0.61)		(1.67)	(1.67)	(0.07)
Exports/sales	---	0.75***	0.75***	0.78***	---	0.995***	0.99***	1.00***	---	0.88***	0.87***	0.91**
		(5.42)	(5.40)	(5.57)		(6.52)	(6.48)	(6.52)		(5.77)	(5.67)	(5.91)
Integrated in a business group	---	0.34***	0.34***	0.34***	---	0.586***	0.59***	0.58***	---	0.39***	0.39***	0.39***
		(3.82)	(3.83)	(3.83)		(5.83)	(5.84)	(5.77)		(3.85)	(3.86)	(3.86)
Foreign capital	---	0.06	0.06	0.05	---	0.258**	0.26**	0.25*	---	0.01	0.02	-0.00
		(0.54)	(0.57)	(0.50)		(2.37)	(2.30)	(2.27)		(0.08)	(0.16)	(-0.04)
% of adopters in industry	---	---	---	4.05***	---	---	---	5.21***	---	---	---	4.973***
				(4.44)				(5.77)				(5.06)
Year 1998	0.38***	0.37***	0.37***	0.07	0.35***	0.36***	0.36***	0.06	0.39***	0.42***	0.43***	0.05
	(4.94)	(4.59)	(4.59)	(0.14)	3.77	(3.58)	(3.59)	(0.57)	(4.46)	(4.63)	(4.65)	(0.40)
Year 2000	0.58***	0.54***	0.54***	0.01	0.54***	0.50***	0.51****	0.03	0.52***	0.56***	0.57***	0.06
	(7.42)	(6.45)	(6.46)	(0.04)	5.89	(4.95)	(4.96)	(0.23)	(5.96)	(5.89)	(5.95)	(0.44)
Industry dummies	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Constant	-1.29***	-1.39***	-1.39***	-2.31***	-2.30***	-2.48***	-2.48***	-2.80***	-3.57***	-4.53***	-4.53***	-3.98***
	(-6.47)	(-4.04)	(-4.04)	(-5.76)	-8.44	(-5.79)	(-5.79)	(-6.46)	(-7.77)	(-8.08)	(-8.09)	(-6.99)
No. observations	4,590	4,590	4,590	4,590	4,590	4,590	4,590	4,590	4,590	4,590	4,590	4,590
Likelihood ratio	424.87***	610.14***	610.34***	630.31***	369.40***	846.20***	846.59***	881.48***	923.04***	1173.96***	1178.25***	1204.30***
Model comparisons (LR test vs. 1)	---	163.33***	163.59***	181.90***	---	387.21***	387.72***	411.21***	---	214.22***	216.19***	237.41***
Model comparisons (LR test vs. 3)	---	---	---	19.71***	---	---	---	33.32***	---	---	---	25.64***

*, **, *** coefficient statistically significant at a 90%, 95% or 99% level; t-ratios in parentheses.

The first issue to point out from Table 4 is that all models estimated present a global fit that is satisfactory, as measured by the Likelihood Ratio. Furthermore, the analysis of the differences between the nested models favours the introduction of the five variables used to measure our hypotheses: in all cases, the augmented models are preferred to the restricted ones, as the Likelihood Ratio tests show.

Our first hypothesis stated that larger firms are more likely to have adopted new technologies. This is, in fact, the case in relation to the three technologies analysed here: size is an important predictor of the likelihood of having adopted numerically controlled machines, robotics and CAD. Having controlled for size, the relevance of financial constraints (hypothesis 2) is only significant in the case of the introduction of robotics. This confirms hypothesis 2 for this technology, given that firms with a higher availability of funds are more likely users of robotics in the production process. The coefficients of this variable are also negative for numerically controlled machines, as expected, but they are not significant at the usually accepted levels. This suggests that investments in robotics may be more difficult to finance externally. Although we cannot clarify the reason why this might be the case, some of the explanations provided above, such as the higher uncertainty surrounding returns on these investments or the larger costs associated, may be the cause.

Interestingly, a higher absorptive capacity (hypothesis 3), measured through the intensity of R&D expenditures, has a positive and significant impact on the likelihood of having introduced all three technologies. The magnitude of this effect is higher for the adoption of CAD than in the case of robotics and CNC, being similar in the last two cases. Finally, the last two estimations for each technology test our last hypothesis (4), namely, that investment in internal R&D is more important for the introduction of new technologies. The results seem to confirm our hypothesis for all three technologies. In all the cases, the coefficient accompanying the ratio of internal R&D to sales is positive and significant, whereas the one that corresponds to R&D carried out externally is non-significant. Again, the pattern of influence shows that internal R&D is more important in the case of CAD and less for the other two technologies.

Taking the full models as reference, the probability of an average firm (the one with all the values of the independent variables evaluated at their means) adopting CNC is 0.422. An increase of one standard deviation in the size variable increases the probability of introducing CNC by 19.03%. Internal R&D is also an important predictor: the probability of adoption increases by 4.3% with the one standard deviation increase. In agreement with the descriptive statistics, the probability of using robotics is less than half that of CNC (0.199).[4] Nevertheless, the impact of the independent variables is much more important. An increase of one standard deviation from mean values, has an impact of 53.51% and 8.1% when the size and internal R&D variables are evaluated, respectively. On the contrary, financial constraints reduce the average probability by 11.07%. Finally, the probability of adopting CAD at mean values is 0.283. In this case, the likelihood of using CAD increases by 30.07% with a one standard deviation in size and by 17,17% with internal R&D intensity.

Regarding the effect of control variables, market structure seems not to have any effect on adoption, given its non-significant coefficient. Nevertheless, there are some differences in adopting behaviour that can be attributed to the sector of activity in which the firm operates (not reported here). Participation in international markets (measured through the exports to sales ratio) also presents non-significant coefficients. This result would be consistent with Lal's (2002) argument that the market is not protected, compelling firms to upgrade their technologies in order to survive. In relation to the remaining firm-specific variables, the fact that the firm is integrated in a business group is positively related to adoption in the three technologies analysed. This effect is clearly more important in robotics, increasing the

[4] This seems consistent with Mansfield's (1988) results that industrial robots were more slowly introduced than numerically controlled machine tools.

probability of adoption of the average firm by 49.52% (the values corresponding to CNC and CAD are 20.01% and 28.69%, respectively). On the other hand, foreign ownership is positively related to adoption only in the case of robotics, not being significant in the other two. Finally, our results are also consistent with the persistence of an epidemic effect. As argued above, as diffusion proceeds in other firms, the likelihood of adopting the technology also increases for a focal firm. For example, taking column 3 as the reference, in the 8 years included in the sample, the probability of the average firm having adopted CNC, robotics and CAD increases by 37%, 50% and 51%, respectively.

Our research on the factors affecting inter firm diffusion continues in Table 5. The developments in the resource-based view of the firm or the refinements of the absorptive capacity concept point to the idea that unobservable firm-specific factors, not captured in the current specifications of our models, could be in operation. Accordingly, the three columns of Table 5 present the estimation of a full random effects logit model. The conclusions of this exercise are very similar to the ones just commented, with firm size and internal R&D showing highly significant and positive effects on adoption[5]. Again, financial constraints are only relevant in the case of one technology, robotics, having, as expected, a negative impact. The pattern of influence is also very similar in the case of our control variables. Both integration in a business group and the proportion of adopters using the technology within the industry positively influence diffusion. However, the presence of foreign capital in the focal firm is only relevant for the case of robotics, having a positive effect. Interestingly, the estimation of rho (bottom of Table 5) is positive and significant, confirming the influence of firm-specific factors in the decision to adopt.

[5] The only exception is the non-significant coefficient for CNC.

Table 5. The adoption of CNC; robotics and CAD in Spanish manufacturing (random effects)

	CNC (10)	Robotics (11)	CAD (12)
Firm size	0.73*** (4.94)	1.48*** (7.95)	0.90*** (5.39)
Firm debt ratio	-0.16 (-0.70)	-0.87*** (-3.30)	-0.09 (-0.34)
R&D intensity (internal)	5.87 (1.59)	8.18** (2.10)	17.92*** (4.42)
R&D intensity (external)	-3.60 (0.58)	1.77 (0.28)	6.12 (0.90)
Market concentration	-0.00 (-0.35)	-0.01 (-0.72)	0.00 (0.24)
Exports/sales	1.21*** (5.16)	1.48*** (5.93)	1.43*** (5.47)
Integrated in a business group	0.41*** (2.91)	0.82*** (5.35)	0.54*** (3.37)
Foreign capital	0.19 (1.14)	0.35** (2.06)	0.09 (0.51)
% of adopters in industry	5.37*** (4.45)	6.92*** (5.91)	7.00*** (5.28)
Year 1998	0.07 (0.49)	0.15 (1.07)	0.16 (1.04)
Year 2000	0.09 (0.46)	0.08 (0.48)	0.16 (0.85)
Industry dummies	Yes	Yes	Yes
Constant	-3.11*** (-5.39)	-3.83*** (-6.32)	-5.57*** (-7.28)
No. observations	4,590	4,590	4,590
Wald test	377.44***	478.54***	578.67***
LR test Rho=0	367.96***	292.53***	404.21***

*, **, *** coefficient statistically significant at a 90%, 95% or 99% level; t- ratios in parentheses.

The last step of our analysis examines the hypothesis that the three technologies are complementary (Stoneman and Kwon, 1994). A crude test of this hypothesis would be to ascertain to what extent the firms using one of the technologies are also using the other two. The correlations between them are positive and show a value of 0.33 for the use of CNC and robotics, 0.37 for CNC and CAD and 0.33 for robotics and CAD. To test this hypothesis more rigorously, a multivariate model is chosen. The estimation is based on the idea that the three technologies (or, at least, two of them) could be complementary. If this were the case, it would seem appropriate to model the decision to adopt as simultaneous equations with possibly correlated errors in which all the decisions depend on the same set of variables. This model is able to take into account the operation of unobservable firm-specific effects affecting the decision to adopt all three technologies. A positive and significant correlation between the errors of the three equations, after having controlled for all the explanatory variables, would offer support for the hypothesis.

Table 6 shows the estimation of this model for three different specifications, taking into account the panel nature of the data. The results are very similar to the ones reported in the logit analysis previously performed, both in sign and significance. Firm size (hypothesis 1) and R&D intensity (hypothesis 3) have a positive influence on the probability of adoption. Again, the separation between internal and external R&D investments shows the relevance of the former and the non-significant coefficient accompanying the latter (hypothesis 4). Financial constraints (hypothesis 2) are only important in the column corresponding to robotics. Finally, integration in a business group and epidemic effects are the key control variables, as in the previous estimations.

Estimates for rho, the correlation of errors between the three equations, are provided at the bottom of Table 6. As we may observe, there are statistically significant correlations between the errors of the CNC, robotics and CAD adoption decisions. The positive sign confirms the intuition behind our crude test: unobservable firm-specific variables increase the probability of adopting all three technologies, confirming the existence of complementarities. In other words, the analysis shows that our specifications are missing some explanatory variables that are simultaneously affecting the decision to adopt all three technologies.

Table 6. A multivariate probit analysis of the adoption of CNC, robotics and CAD in Spanish manufacturing (robust standard errors)

	CNC (1)	Robotics (2)	CAD (3)	CNC (1)	Robotics (2)	CAD (3)	CNC (1)	Robotics (2)	CAD (3)
Firm size	0.31***	0.57***	0.38***	0.31***	0.57***	0.38***	0.30***	0.57***	0.37***
	(3.63)	(4.87)	(3.37)	(3.63)	(4.77)	(3.38)	(3.55)	(4.82)	(3.26)
Firm debt ratio	-0.06	-0.32***	0.06	-0.06	-0.32***	0.06	-0.06	-0.33***	0.07
	(-0.57)	(-2.94)	(0.54)	(-0.57)	(-2.94)	(0.54)	(-0.59)	(-2.98)	(0.62)
R&D intensity	2.79**	4.16***	6.88***	---	---	---	---	---	---
	(2.13)	(3.01)	(5.01)						
R&D intensity (internal)	---	---	---	3.19*	4.44**	8.33***	3.11*	4.47**	8.23***
				(1.89)	(2.52)	(4.33)	(1.84)	(2.54)	(4.28)
R&D intensity (external)	---	---	---	1.78	3.46	2.87	1.98	3.20	3.02
				(0.70)	(1.13)	(1.01)	(0.77)	(1.06)	(1.07)
Market concentration	-0.00	-0.00	0.01*	-0.00	-0.00	0.01*	-0.00	-0.00	-0.00
	(-0.57)	(-0.72)	(1.77)	(-0.57)	(0.72)	(1.74)	(-0.23)	(-0.79)	(-0.14)
Exports/sales	0.46***	0.61***	0.51***	0.46***	0.61***	0.50***	0.47***	0.61***	0.53***
	(4.45)	(5.71)	(4.58)	(4.43)	(5.70)	(4.53)	(4.57)	(5.72)	(4.76)
Integrated in a business group	0.23***	0.37***	0.24***	0.23***	0.37***	0.25***	0.23***	0.37***	0.25***
	(3.60)	(5.46)	(3.52)	(3.60)	(5.47)	(3.55)	(3.60)	(5.40)	(3.77)
Foreign capital	0.03	0.16**	0.02	0.03	0.16**	0.02	0.03	0.15**	0.00
	(0.48)	(2.07)	(0.21)	0.49	(2.07)	(0.25)	(0.43)	(1.99)	(0.05)
% of adopters in industry	---	---	---	---	---	---	2.475***	3.00***	3.18***
							(5.35)	(6.87)	(6.42)
Year 1998	0.22***	0.21***	0.24***	0.22***	0.21***	0.24***	0.01	0.04	-0.00
	(5.21)	(4.44)	(5.31)	5.21	(4.44)	(5.31)	(0.11)	(0.84)	(-0.00)
Year 2000	0.32***	0.30***	0.33***	0.32***	0.30***	0.34***	-0.00	0.02	0.01
	(6.91)	(5.77)	(6.73)	6.92	(5.77)	(6.76)	(-0.00)	(0.37)	(0.13)
Industry dummies	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Constant	-0.82***	-1.39***	-2.51***	-0.82***	-1.39***	-2.51***	-1.38***	-1.60***	-2.16***
	(-3.99)	(-5.91)	(-9.12)	(-3.99)	(-5.91)	(-9.10)	(-5.99)	(-6.68)	(-7.81)
Rho21	0.40*** (15.24)			0.40*** (15.24)			0.40*** (15.20)		
Rho31	0.43*** (17.26)			0.43*** (17.19)			0.43*** (17.22)		
Rho32	0.41*** (14.98)			0.41*** (14.98)			0.41*** (15.02)		
No. observations	4,590			4,590			4,590		
Wald Test	1316.05***			1326.43***			1392.53***		
LR test of Rho2,1=Rho3,1=Rho3,3=0	666.61***			664.72***			664.06***		

*, **, *** coefficient statistically significant at a 90%, 95% or 99% level; t-ratios in parentheses.

6. CONCLUSIONS AND DISCUSSION

This paper presents an empirical analysis of the adoption behaviour of a sample of Spanish firms belonging to the Spanish manufacturing sector. Our analysis pays special attention to the influence of firm-specific variables and the interdependences between technologies for explaining the introduction of numerically controlled machines, robotics and computer aided design. Our results offer general support to the hypotheses developed in this research, with relative independence of the technology under analysis.

The estimations confirm the role of firm size, financial constraints and absorptive capacity in explaining the adoption behaviour of manufacturing firms in Spain. As is also evident in previous research, our results confirm that larger firms are more likely to be adopters of new process technologies. Although the availability of data did not allow us to search for alternative explanations that could explain this association (Astebro, 2002), we were able to independently assess the role of financial constraints. This variable only contributed to the explanation of diffusion in the case of robotics, not being relevant for the other two technologies. The capacity of a firm to absorb new technology did play a significant role at explaining adoption patterns. Firms investing a relatively large amount of money in R&D activities were the ones that also showed a greater likelihood of having adopted the new process technologies. Moreover, investments in internal R&D have a consistent positive effect on adoption, while those performed externally do not show any impact.

A number of control variables have been shown to positively influence adoption. A higher exposition to external markets through commercial activities and belonging to a business group increase the probability of adoption. Foreign capital is only relevant in the case of robotics. Finally, epidemic effects are consistently present in our results, showing the importance of information flows and uncertainty reduction for the decision to introduce the new process technology.

Our results have a number of implications for research on the study of innovation diffusion. First, they seem to point to the importance of the costs associated with the decision to adopt a new technology. Buying equipment, restructuring the production process or learning how to use the new technology may impose an additional constraint to other impediments to using it. In fact, the costs associated with new technology introduction have been shown to be one of the most important obstacles to its use in manufacturing (Baldwin and Lin, 2002). Nevertheless, our results, in which only the coefficient associated with robotics is significantly different from zero, lead us to think that its relevance may be dependent on the type of technology under analysis. More complex and more expensive technologies are expected to be the most difficult to finance. Consistent with our results is the finding that investment in robot technologies shows higher volatility than in machine tools in general (Stoneman and Toivanen, 2000). Similarly, Mansfield (1988) reports that the average rate of return on investment in robots by the companies in his sample was lower than for other innovations, including numerically controlled machines.

Second, our estimations have recovered the original idea of Cohen and Levinthal (1989, 1990) that *internal* R&D investments affect absorptive capacity. Moreover, our research has attempted to address the trickier question as “to whether absorptive capacity needs to be internally developed or to what extent a firm may simply buy it” (Cohen and Levinthal, 1990: 135) in a context of new technology adoption. As Cohen and Levinthal (1990) hypothesise, our results suggest that the capacity of R&D external investments to contribute to developing absorptive capacity is limited. As argued above, the use of new process technologies requires the integration of the innovation within the activities being developed inside the firm. Those activities frequently involve complex, firm-specific routines or capabilities whose knowledge needs to be integrated with the product of R&D investments in order to promote an effective improvement of absorptive capacity. The tacitness of these activities and the effort needed to integrate knowledge into these processes provide additional reasons why internal R&D activities should be more effective. Only in this way could firms enhance their capability to understand, evaluate, assimilate and exploit new process technologies.

Our results on the absorptive capacity concept also contribute to shed light on the discussion about the information capacity conjecture (Jensen, 1988). This hypothesis states that "greater capacity to obtain and evaluate information should result in faster learning about the innovation" and faster adoption. Nevertheless, "empirical tests for it often show little or no statistically significant effect" (Jensen, 1988: 335). In fact, several of the papers using R&D intensity as a measure for information capacity have failed to show positive results (see, for example, Globerman, 1976 or Karshenas and Stoneman, 1993). Although, our estimations do not invalidate the fact that delay in adoption may result from a higher information capacity (Jensen, 1988), we suggest that researchers on the diffusion of innovations explicitly consider the difference between internal and external R&D when estimating models of adoption.

Third, given our estimations, the introduction of firm effects into diffusion analysis seems to be essential. Both the random effects estimator and the multivariate technique used point to the difficulties of correctly and fully specifying the determinants of the adoption decision. Even when data are available, the measurement of some concepts at the firm level has proved elusive. For example, the concept of absorptive capacity not only depends on R&D investments, but also on several other firm attributes, such as the existence or effectiveness of communication channels. The possession of data on all these attributes seems difficult to achieve. This, again, suggests the importance of unobservable variables in strategic management research (Godfrey and Hill, 1995).

Finally, our results provide clear evidence underpinning the hypothesis that the adoption of one of the technologies analysed here is positively related to the introduction of the other two. This conclusion is in line with the one previously reached by Stoneman and Kwon (1994). Nevertheless, the question remains whether this effect is due to the existence of complementarities in the production process between the three innovations analysed, the existence of other firm-specific effects increasing the probability that a firm adopts any new technology or a combination of both. Therefore, although they seem to show the importance of complementarities between the technologies, further research should be undertaken on the specific reasons that can explain it.

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