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Intrafirm diffusion of new technologies: an empirical application

Lucio Fuentelsaz, Jaime Gomez*, Yolanda Polo

Departamento de Economía y Dirección de Empresas, Universidad de Zaragoza, Gran Vía 2, 50005 Zaragoza, Spain

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Abstract

Research on the diffusion of new technologies has centred on the study of the interfirm rate of diffusion, paying much less attention to intrafirm aspects. This paper attempts to overcome this gap in the literature by analysing the factors that influence the speed with which a new technology, the ATM, is fully adopted. The data over which the hypotheses are tested belongs to the Spanish savings banks market. The results show that the rate of intrafirm diffusion is explained by innovation, firm and market characteristics. In testing our hypotheses we make use of both traditional methods and survival analysis techniques.

Keywords: New technology; Intrafirm rates of diffusion; ATM; Savings banks; Survival analysis

1. Introduction

Technological progress fundamentally depends on the adoption of new technologies. However, firms neither immediately nor fully adopt them. From a microeconomic perspective, two questions are central to the diffusion debate: (1) What factors influence the adoption of new technologies by the firms operating in a market? (2) What are the factors that influence the speed with which firms tend to fully employ the new technology once they have adopted it? Whereas the first question refers to the interfirm rate of diffusion of new technologies and has been a frequent topic of research, much less attention has been paid to the study of the intrafirm rates of diffusion. This is surprising, given that the study of the extent of use of a technology within a firm is at least as important as the study of the number of users of that technology (Stoneman, 1981).

The importance of covering this gap in the literature should be emphasised. Given that the great majority of the innovations are divisible, the initial adoption decision constitutes just the first step in a more complex and longer diffusion process by which the potential beneficial effects of a new technology are fully realised to the benefit of society. As Stoneman (1981) points out, this is especially important in a world populated by large firms, in which the initial adoption decision only supposes a small percentage in aggregate terms. This is, in fact, the case in most of the latest technologic advances (microcomputers, mobiles, automated teller machines (ATM) or teleprocess terminals) associated with information processing needs.

Consequently, the objective of this paper is to provide evidence on the factors affecting the speed at which new technologies diffuse within firms. In order to test the predictions suggested by the theory, we examine the characteristics of the diffusion of a new product and process technology, the ATM, on a sample of Spanish savings banks. This technology has been the subject of several studies (Hannan and McDowell, 1984a,b, 1986; Ingham and Thompson, 1993; Maudos,

* Corresponding author. Tel.: +34-976-761-000; fax: +34-976-761-767.
E-mail addresses: lfuente@posta.unizar.es (L. Fuentelsaz), jgvillas@posta.unizar.es (J. Gomez), ypolo@posta.unizar.es (Y. Polo).

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1994; Saloner and Shepard, 1995). However, no attempt has been made to consider its intrafirm diffusion aspects.

The data available for the analysis possesses two important features that are relevant for our analysis. First, as in Ingham and Thompson (1993), the sample we consider is relatively homogeneous in terms of resources and capabilities, which has been suggested as an interesting feature in view of the investigation of firm level effects. Second, the Spanish banking sector has been subject to changes that have affected the configuration of the sector in terms of the behaviour of the financial entities and the structure of the market. The elimination in 1989, of the restrictions that prevented savings banks from operating all over the country has transformed the context in which they perform their activities. As a consequence, the wave of mergers and acquisitions that took place and the expansion process that led some financial entities to open new branches in new geographical markets is expected to have influenced innovation and diffusion rates. The possibility of delimitation of the geographical market in which a savings bank operates provides us with interesting data on which to perform our analysis.

In testing our hypothesis, we make use of both traditional and survival analysis methods. Although, survival analysis techniques have been applied to the study of adoption probabilities, no attempt has been made to evaluate the factors affecting the time elapsed from adoption to full internal diffusion. As Karshenas and Stoneman (1995) suggests, if different states in the internal adoption process are defined, duration models may be used to estimate the time up to a concrete level of diffusion. These models are especially appropriate in those cases in which both the cross-section side and the longitudinal side (time) of the data are available (Fuentelsaz et al., 2002a). Following this recommendation, a proportional hazards model is employed to evaluate our hypotheses.

The paper is organised as follows: Section 2 reviews the literature on intrafirm diffusion, distinguishing between those modelling efforts that have been based on the epidemic tradition and those more reliant on a decision-theoretic approach. Section 3 proposes the set of hypotheses that are tested. Section 4 presents the dynamic market potential model that is used to estimate the rates of intrafirm diffusion and explains the econometric strategies followed. Section 5 describes the sample of Spanish savings banks on which the analysis is performed. Section 6 shows the results of the estimation of the ordinary models and survival regression models proposed and, finally, Section 7 concludes.

2. Literature review

Microeconomic research on the factors affecting the diffusion of new technologies has concentrated on the analysis of two main dimensions, namely, interfirm and intrafirm. The first of these has been concerned with the study of the number of firms using an innovation and has been the subject of frequent theoretical and empirical attention. On the other hand, the intrafirm dimension has concentrated on measuring the extent of which a firm uses a new technology once the initial adoption decision has been taken. Contrary to the interfirm case, activity has been much less both theoretical and empirically and has focused on the effect of demand factors.

From a theoretical point of view the literature on intrafirm diffusion may be divided into two groups of models: epidemic and decision-theoretic (Karshenas and Stoneman, 1995). The main difference between both approaches is that the latter is more explicitly choice-theoretic. As the diffusion process develops, the experience of firms with new technology leads them to update initial estimates of both risk and returns and the level of use of the new technology (Karshenas and Stoneman, 1995).

The epidemic models have mainly been used in the analysis of the interfirm dimension of diffusion, although some applications are also found in the intrafirm case. The most important hypothesis underlying them is that the rate at which an innovation diffuses is directly proportional to the gap existing between the number of potential adopters and the cumulative number of adoptions. This assumption is consistent with the traditional finding of an S-shaped diffusion curve characteristic of most diffusion studies.

Three particular cases are distinguished from the general one, depending on the form assumed for the coefficient of diffusion (Majahan and Peterson, 1985). The *external influence model* assumes diffusion to be driven by factors outside the social system. The model is more appropriate in situations characterised by a low degree of interaction between the components of the system and in which the main flows of information are provided by external and structured sources of communication (e.g. government agencies, sales people, ...). In the *internal influence model*, the diffusion process is exclusively explained by interpersonal contacts. That is, the rate of diffusion is explained by the interaction of three elements: prior adopters, potential adopters at time *t* and an index of imitation. Finally, a last type of models, *mixed-influence models*, attempt to combine both internal and external effects through the inclusion of a coefficient of diffusion that takes a more complex form.[1]

Epidemic type models are based on several assumptions which are not always realistic and have been criticised by several authors. The main criticisms are based on the lack of microeconomic foundations in their development (Stoneman, 1981). In spite of the objections, research efforts have mainly concentrated on designing a number of modifications that incorporate extensions to the basic models. Examples, include models that incorporate a dynamic ceiling on the maximum number of adopters (Majahan and Peterson, 1978), flexible diffusion models (Floyd, 1968) or models that integrate both the spatial and time dimension in their analysis (Mahajan et al., 1979).

Nervertheless, other authors have departed from Epidemic Models and have preferred decision theoretic approaches. Following Feder et al. (1985) a theoretical framework for analysing adoption and diffusion processes at the firm level should include a model of the entrepreneur's "*decision making about the extent and intensity of use of the new technology at each point ... and a set of equations of motion describing the time pattern of parameters that affect these decisions*". These equations of motion should incorporate changes in the model parameters over time, resulting from dynamic processes affecting information levels, learning by doing or credit access.

Some of the criticisms have been overcome by work that has modelled the process of decision making under uncertainty (Stoneman, 1985). These models have mainly been developed in the context of the adoption of agricultural innovations in developing countries. Most of the papers have used static analysis, relating the degree of adoption to the factors that affect it (Feder et al., 1985), and have followed Mansfield's work in characterising the problem as one in which a new technology substitutes the old one.

A small number of these papers have focused on the effect of learning and new information on the intrafirm diffusion process. Lindner et al. (1979) is an example in which a Bayesian mechanism is used to achieve such an objective. A version of this type of models has been developed by Stoneman (1981) for the case of industrial innovations. Stoneman proposes a choice of technique-theoretic model in which the level of full adoption is determined endogenously. The model is shown to have the characteristic S-shape form found in diffusion studies and it is consistent with Bayesian learning. According to it, the entrepreneur decides between the old and the new technology by maximising a utility function in which the firm incurs the cost of adjustment every time the internal level of adoption is changed. Initially, the firm sets out with an estimation of risk and returns stemming from the new technology. As diffusion proceeds the entrepreneur learns from experience with the new technology, adjusting the expected returns and better estimating the risk supported.

This literature is complemented by other approximations. In spite of the fact that they do not especifically tackle the issue of intrafirm diffusion, they provide us with a richer vision of the factors affecting the process. Perhaps the main alternative to epidemic models is represented by probit models (Geroski, 2000). Far from relying on information diffusion aspects, probit models centre on differences among individuals or firms to explain diffusion patterns. These arguments are similar to the ones proposed by evolutionary approaches to innovation diffusion (Nelson and Winter, 1982; Silverberg et al., 1988; Metcalfe, 1998) in which the heterogeneity of the agents also arises as a key determinant (Geroski, 2000). Nevertheless, the distinguishing feature of the latter is the substitution of equilibrium concepts and individual optimisation by an emphasis on limited information and bounded rationality (Karshenas and Stoneman, 1995; Metcalfe, 1995). A last group of models base their explanation of why new technologies are slowly adopted on the information generated by the use of the innovation by other firms (Geroski, 2000). Although, they mainly centre on how technologies are selected, they also help to understand the appearance and the

[1] Geroski (2000) presents an excellent explanation on the foundations of these models.

influence of "bandwagon" and "penguin" effects on the diffusion curve, particularly when network externalities are present (Geroski, 2000; Choi, 1997).

Finally, some authors have studied the diffusion process from a sociological perspective (Rogers, 1995; Valente, 1995). Rogers (1995) underlines the importance of the characteristics of the innovation (relative advantage, compatibility, complexity, triability and observability) as key determinants of adoption rates. Nevertheless, he also highlights the relevance of other factors as the nature of communication channels and the characteristics of the social system in which information (and the innovation) diffuses. This emphasis is similar to the one of social network analysts, who make diffusion processes to be crucially influenced by the interactions taking place among actors in the social system and the communication patterns arising between them (Coleman et al., 1966; Valente, 1995).

In a similar vein, the empirical literature on the determinants of intrafirm diffusion has been scarce and mainly dominated by the application of models of the epidemic type. The interest has centred on the study of the factors that explain the S-shape and affect the speed of intrafirm diffusion. Mansfield (1963) applies an epidemic model to the study of the speed of substitution of steam locomotives for diesel ones in the US, whereas Romeo (1975) analyses the diffusion of numerically controlled machine tools in 10 industries in the US.[2] Taken together, the evidence seems to confirm the hypothesis of the model, pointing out that the processes of interfirm and intrafirm diffusion share common features (Mansfield, 1963).

This evidence is complemented with a more descriptive analysis presented in two additional studies. Nabseth and Ray (1974) analyse the internal diffusion of special presses in paper making at both the plant and firm level. Their main conclusion is that expected profitability plays a very important role at explaining intrafirm diffusion. By using data from 19 steel plants, Schenk (1974) finds the rate of intrafirm diffusion of continuous casting to be negatively affected by firm size. Globerman (1976) studies the effect of firm size and year of adoption on the number of years it took for 100% of a firm's output to be produced on machines equipped with special presses.[3] The estimated relationship is consistent with the Mansfield model and shows that both firm size and year of adoption do have the expected effects on the time to full internal diffusion.

Antonelli (1985) studies the internal diffusion of technology in an international context. Firm size is, again, negatively related to the rate of intrafirm diffusion. The time lag of adoption, a centralised structure and the internal origin of the innovation present a positive influence on diffusion. Similarly, Polo (1987) uses the model proposed by Mansfield (1961) in order to analyse the internal diffusion of teleprocess terminals in the Spanish banking sector. The results for the sample of banks and savings banks confirm previous empirical findings in relation to the influence of firm size and the time lag of adoption over intrafirm rates.

The last study considered in this review is the one by Levin et al. (1992). The distinguishing feature of their research is that they attempt to investigate the structural factors of markets affecting the intrafirm rate of diffusion. Together with some of the variables already included in other studies, they examine the effect of market concentration on the internal adoption of optical scanners through the stores of firms located in different geographic markets across the US. The results confirm that intrafirm diffusion takes place more rapidly when the profitability of the innovation is greater and the costs are lower. Market concentration and firm market share have a negative effect on the speed of internal diffusion, confirming the effect of uncertainty hypothesised by the Stoneman choice-theoretic model. Store size and order effects positively influence the diffusion process, whereas the presence of key rivals in the market has a negative impact. Finally, in agreement with previous research,

[2] Mansfield (1963) is the first author to propose a specific epidemic type model directed to study the intrafirm dimension of the diffusion process. He uses a pure internal influence model, assuming that the coefficient of intrafirm diffusion is affected by a set of factors considered to be relevant (profitability and uncertainty of the new technology, liquidity and firm size). Mansfield also tests the influence of the following factors: age of the old locomotives, absolute number of locomotives necessary to go from 10 to 90% of intrafirm diffusion, average haul of the railroad and firm profitability.

[3] Other factors considered were the average age of the machines in place, the proportion that newsprint comprised of total output, the number of paper machines operated by the firm and firm ownership status.

the size of the firm is shown to be negatively related to the rate of intrafirm diffusion.

3. Hypotheses

The hypotheses that are tested in this paper are limited by the characteristics of our sample and the availability of data. They draw on the literature on innovation and new technology diffusion and, specifically, on the papers reviewed in the previous section. Accordingly, the hypotheses proposed refer to the innovation, the firm and the market in which it operates.

3.1. Expected profitability and uncertainty surrounding the innovation

Expected profitability and uncertainty are common elements of models that study investment behaviour of firms. In consequence, these two components are also present in both the epidemic and the choice-theoretic modelling of the intrafirm diffusion process. All the models assume that an innovation will appear more attractive to a firm the higher the expected profitability from using it. Given this, the main concern of researchers has centred on either finding a way of correctly measuring this concept, or choosing an appropriate proxy for it. The main difference on the role of profitability between the two approaches reviewed before is, again, in terms of the degree of formalisation of the decision process within the firm. Mansfield's work assumes the relationship between profitability and the rate of intrafirm diffusion to be true, whereas Stoneman's derives the positive relationship from his choice of technique model.

Much less agreement is found in the theoretical literature when the effect of the uncertainty surrounding the innovation is studied. It is the fact that almost any investment is, at least, partially irreversible that makes uncertainty so relevant (Pindyck, 1991). Provided that strategic factors do not compel the innovator to quickly spend money in acquiring the innovation, the effect of uncertainty may be reduced by the option the firm has to wait for new information to arrive. As hypothesised by the epidemic models, this information may be seen arriving from either sources of information originated in the social system in which the diffusion process is taking place or from external channels of communication. According to this, we would expect the firm would delay adoption whenever uncertainty is high and/or a substantial reduction of it is expected in the following period. Nevertheless, when strategic aspects are important, this option to delay investment may not be so feasible and pre-emption may arise as a more relevant issue to consider.

As in the case of profitability, both epidemic and decision models consider uncertainty an important factor at the time of explaining the rate of intrafirm diffusion. In this case, however, opposite effects are proposed. Whereas Mansfield's predictions are negative, the influence of uncertainty on intrafirm diffusion in Stoneman's model is positive (Levin et al., 1992). The empirical evidence (Mansfield, 1963; Romeo, 1975; Levin et al., 1992) shows that the reduction of uncertainty is positively related to diffusion, at least when the time elapsed from the moment in which the first firm in the industry adopted the innovation is considered. According to this, we should expect the delay in adoption to positively influence the rate of intrafirm diffusion. This will be the effect hypothesised in this research.

Hypothesis 1. The profitability of the innovation is expected to have a positive effect on the rate of intrafirm diffusion.

Hypothesis 2. The reduction of the level of uncertainty surrounding the innovation is expected to have a positive effect on the rate of intrafirm diffusion.

3.2. Firm size and fund availability

The study of diffusion of new technologies has largely been concerned with the effect of large firm size on technical progress. This interest derives from the Schumpeterian hypothesis that "large firms are more than proportionately more innovative than small firms" (Kamien and Schwartz, 1982, p. 22). Although, it is not clear whether this effect was, in fact, proposed by Schumpeter (Cohen and Levin, 1989; Kamien and Schwartz, 1982), it has motivated a growing body of literature that attempts to check the validity of the proposition. In this context, the literature on diffusion has also concentrated on analysing the influence of firm size on the shape of the diffusion curve. The interest has been to ascertain whether large firms are quicker to adopt new technologies than small ones.

It is generally assumed that bigger firms lead the innovation and diffusion processes due to the existence of economies of scale and scope in R&D activities and in the application of their results (Buzzachi et al., 1995). Given that large firms have a larger volume of sales than their smaller counterparts, they are supposed to be able to spread the fixed cost invested in innovation over a higher number of units (Cohen and Levin, 1989). A second argument focuses on the existence of capital market imperfections to justify the proposed positive effect. If the availability of internal funds is higher in bigger firms they should be able to finance the investment associated with innovation and diffusion processes and engage in these activities. A similar argument is the one that points to the fact that more profitable entities are able to secure the stable need of funds required. Other authors suggest the idea that large companies are more likely to possess the specialised complementary assets required for the commercial success of innovations (Teece, 1986; Buzzachi et al., 1995).

Counterarguments focus on the loss of managerial control in large firms (Cohen and Levin, 1989) and the fact that they may suffer from what has been termed structural inertia (Crozier, 1964). This would make bigger firms the slowest at diffusing the new technology. The empirical evidence for the case of the diffusion of new technologies tends to confirm a positive effect on size when the initial adoption decision of firms is considered. This evidence is especially convincing in the case of the adoption of ATMs in banking. Several papers (Hannan and McDowell, 1984a,b, 1986; Sharma, 1993, Buzzachi et al., 1995) prove the positive influence of firm size on the probability of adoption of ATMs. However, this positive relationship is not restricted to banking and examples are also found in the electric utility industry (Rose and Joskow, 1990) or in the engineering and metalworking industries (Baptista, 2000).

In the case of intrafirm diffusion, however, the theoretical arguments and the empirical evidence point in the opposite direction. Firm size is expected to have a negative effect on the rate of diffusion when the analysis centres on the rate at which diffusion proceeds internally. Romeo (1975) indicates two reasons for this effect. First, the absolute level of investment necessary to achieve a concrete degree of internal diffusion is lower in smaller firms. Second, processes of decision-making may be slower in bigger firms. This second reason seems to be along the lines of some of the counter arguments mentioned before for the case of the interfirm diffusion. The empirical evidence (Romeo, 1975; Globerman, 1976; Levin et al., 1992) shows, in fact, that this negative effect is in operation when intrafirm aspects are considered.

Another difference with the literature of interfirm diffusion is that economies of scale and scope and market imperfection arguments are analysed separately. Therefore, whereas firm size is expected to have a negative effect on the rate at which innovations diffuse internally the availability of financial resources is expected to have a positive influence. This positive effect seems to have been confirmed empirically. Both Romeo (1975) and Mansfield (1963) find a positive influence of liquidity on the rate of intrafirm diffusion. Therefore, in this paper we attempt to discern between these two competing effects.

Hypothesis 3. Firm size is expected to have a negative effect on the rate of intrafirm diffusion.

Hypothesis 4. The availability of financial resources is expected to have a positive effect on the rate of intrafirm diffusion.

3.3. Market structure

Together with firm size, the relationship between market structure and innovative behaviour has been one the main concerns for economists and policy makers. As in the case of the previously analysed variable, Schumpeter (1970) suggests a positive relationship between market concentration and innovative activity. The possibility available to the innovator to exert market power would provide him with the incentives to undertake the investment required.

Some authors propose that this positive influence of market structure on innovation is also valid for the diffusion case, although, monopoly structures are explicitly excluded (Gatignon and Robertson, 1989). A more concentrated market would allow firms to better capture consumer value than a less concentrated market, providing incentives for early adoption (Saloner and

Shepard, 1995). Nevertheless, the counterargument seems to centre on the fact that this higher concentration would, however, undermine the pressures to adopt exerted by the existence of higher levels of competition.[4] Therefore, as Reinganum (1981) points out, the reasoning should attempt to reconcile the conflicting effects between the expected positive effects of competitive pressures and appropriability.

All this theoretical background is complemented with the one that suggests that the relationship between diffusion and market structure may be best captured through a quadratic specification. In fact, this quadratic relationship has been hypothesised by Kamien and Schwartz (1982) modelling of the adoption on innovations and has proved valid in a number of empirical studies investigating the link between market structure and innovation activity (Cohen and Levin, 1989; Espitia et al., 1991).

In the case of intrafirm diffusion, arguments against and in favour of a positive relationship between market structure and internal diffusion tend to centre on uncertainty and the pressures to adopt exerted by competition. The prediction of the Stoneman model regarding uncertainty is one of a direct relationship with technological progressiveness. Market concentration should reduce uncertainty, lowering intrafirm diffusion rates. In a similar vein, Mansfield (1968) points out a positive relationship between competition intensity and adoption. Following the Schumpeterian hypothesis, monopoly power should be positively related to innovation. In this case, the empirical evidence is even more scarce. In the only available study (Levin et al., 1992) concentration is shown to be negatively related to the rate of intrafirm diffusion of optical scanners in grocery stores. Thus, our last hypothesis takes the following form:

Hypothesis 5. Market concentration is expected to have a negative effect on the rate of intrafirm diffusion.

Table 1 summarises the hypotheses that have been proposed and will be tested in this research.

[4] Quirmbach (1986) points out that in those markets where collusive behaviour takes place, diffusion will proceed more slowly. This solution seems to be more feasible in more concentrated structures.

Table 1
Hypotheses and expected effects

Hypothesis	Expected effect on intrafirm diffusion
H1: expected profitability	+
H2: uncertainty	−
H3: firm size	−
H4: availability of funds	+
H5: market structure	−

4. Model and econometric strategy

4.1. The traditional approach

The empirical studies investigating on the factors affecting the intrafirm rate of diffusion have traditionally relied on a two-stage procedure (e.g. Mansfield, 1963, Levin et al., 1992). The method proceeds as follows. In the first stage, the parameters of intrafirm diffusion are estimated for every firm, given the data on the number of new units of the old technology acquired. The parameters obtained in this way are then used as the dependent variables in a second stage in which the influence of the factors highlighted in Section 3.3 is evaluated.

To follow this approach, a description of how the diffusion process evolves is first needed in order to obtain the parameter that gives the speed of internal adoption for each firm. To this end, researchers have generally used models of an epidemic type. The main reason seems to be the excellent results they provide in terms of goodness of fit and simplicity. In our case, the intrafirm diffusion process is modelled through the "fundamental diffusion model" (Majahan and Peterson, 1985):

$$\frac{dN(t)}{dt} = g(t)[\bar{N} - N(t)] \qquad (1)$$

where $(dN(t)/dt)$ is the rate of diffusion at time t, $g(t)$ is the coefficient of diffusion, which includes the factors determining the decision on the extent of use of the new innovation, $N(t)$ is the cumulative number of adopters at time t and $\bar{N}$ is the total number of potential adopters in the social system.

This is the epidemic internal-influence model used by Mansfield (1963) and Griliches (1957), which gives the classical logistic curve for the number of cumulative adoptions.[5] One of the main limitations of this model for our purposes is that the maximum number of adopters is expected to remain constant throughout the diffusion process. Although, this assumption could seem plausible in a relatively stable population of potential adopters, it seems unrealistic in the general case and, particularly, in our sample. We would expect the number of potencial adopters either to increase or decrease over time depending on different relevant factors.

A modification of the model that takes into account a dynamic potential adopter population has been proposed by Majahan and Peterson (1978). Their proposal allows for changes in the maximum number of potential adopters over time. According to this, $\bar{N}(t)$, the dynamic maximum number of adopters, is hypothesised to depend on a vector of relevant variables, $B(t)$, in the following way:

$$\bar{N}(t) = f[B(t)] \tag{2}$$

Substituting (2) into the fundamental diffusion model (1) yields

$$\frac{\mathrm{d}N(t)}{\mathrm{d}t} = bN(t)(f[B(t)] - N(t)) \tag{3}$$

The discrete analogue to model (3),

$$N(t+1) = (bf[B(t)] + 1)N(t) - bN^2(t) \tag{4}$$

may be used to estimate the parameter of intrafirm diffusion, b, as "minus" the coefficient accompanying the $N^2(t)$ regression term.[6]

The approach followed in this paper takes expression (4) as the starting point. This discrete analogue version of the model is first used to estimate the parameter of intrafirm diffusion for each firm, b, by OLS. The estimated intrafirm diffusion rate for each firm is then used as the dependent variable in a second OLS regression (correcting for heteroskedasticity,[7] White (1980)) in which the explanatory variables suggested by the literature are included.[8]

4.2. Survival analysis

In this research, a different econometric strategy is also used. We estimate a survival model of the type proposed by Cox (1972, 1975). Survival or duration models have been used in the diffusion literature to study the time up to first firm adoption of a new technology (for a recent application, see Baptista, 2000). In these models, the time from the moment in which the new technology is available in the market to first adoption is specified as a function of innovation, firm and market characteristics. No attempt, however, has been made to incorporate these techniques into the analysis of the speed at which intrafirm diffusion takes place. The use of duration models in this case seems a natural extension of their application in interfirm studies. Karshenas and Stoneman (1995) suggests that, if different states in the internal adoption process are defined (for example, in terms of percentage of share of output produced by the new technology), duration models may be used to estimate the time up to a concrete level of adoption.

Survival models have a clear advantage over traditional regression alternatives (e.g. MCO, logit or probit). First, they provide the researcher with the possibility of using all the information when longitudinal data is available. Second, they also have the ability to handle censored observations (in the case of intrafirm diffusion, those corresponding to organizations for which the process of internal diffusion is not complete). Finally, in some contexts they also provide the researcher with a way of exploring alternative

[5] As Levin et al. (1992) point out, the assumption for an S-shaped diffusion process is consistent with an economic model of firm behavior optimisation, as demonstrated by Stoneman (1981). In addition to the logistic curve, other functions (e.g. Gompertz) were used at modelling the cumulative number of adoptions. Nevertheless, the logistic curve was shown to be the most effective at describing the internal diffusion process.

[6] We retain the assumption of a fixed "b". As Levin et al. (1992) explain, this is reasonable as long as the new technology is simple.

[7] The problems attached to the use of this methodology and the reason to use White (1980) technique are further explained in Levin et al. (1992).

[8] To apply the first step of the procedure data on the number of cumulative number of adoptions of each firm, $N(t)$, and on the variables explaining the evolution of the potential market, $B(t)$, are needed. The second stage of the estimation regresses the coefficients of intrafirm diffusion obtained in the first step on cross-sectional data containing information on the variables suggested by the literature (Fuentelsaz et al., 2002b).

specifications to the S-shaped diffusion curve.[9] In these models, the dependent variable is the time elapsed, or duration, between a starting point and an event of interest.

The model that will be used in this research is the Proportional Hazards Model proposed by Cox (1972). The reason to use it is that it gives very efficient estimates as compared to a parametric proportional hazards model, not requiring any underlying distribution to be specified. The main assumption of the model is that the hazard functions of all the individuals are a multiple of an unspecified baseline hazard function (Fuentelsaz et al., 2002a). In its continuous type version the model is specified as follows:

$$\lambda(t; Z_i) = \lambda_0(t) r_i(t) \quad (5)$$

where $r_i(t) = \exp(\beta Z_i(t))$ is referred to as the risk score for the ith subject, β is a vector of regression parameters and $\lambda_0(t)$ is the baseline hazard function incorporating the random element. The model does not include a constant term because it is incorporated in $\lambda_0(t)$. The expression $\beta Z_i(t)$ incorporates the influence of the covariates $Z_i(t)$ over the hazard rate. As we have seen in Section 3, the literature on intrafirm diffusion has suggested that these covariates are mainly related to firm-specific and innovation-specific characteristics. Their definition as time dependent covariates allows for the relaxation of the constancy assumed for some of the variables in theoretical and empirical models.[10] Following Levin et al. (1992), in this research the $Z_i(t)$ is also extended to include the influence of market and competitor factors.

5. Data and variables

As mentioned in the introduction, the data available for the empirical analysis refers to the diffusion of a product and a process innovation (Ingham and Thompson, 1993), the ATM, through the distribution channels of a sample of Spanish savings banks during the period from 1981 to 1998.[11] ATMs are electro-mechanical devices that permit bank customers to make deposits and withdraw cash from their accounts and access other services, such as balance enquiries, transfer of funds or acceptance of deposits (European Central Bank, 2000). As a process innovation they substitute for labour, whereas as a product innovation they provide a service not restricted to opening hours.

Public data are used in our study. It comes from the Bank of Spain and the Spanish Savings Banks Confederation. Information on the explanatory variables and on the number of units of ATMs installed in each entity is provided every end of a year. Therefore, the number of ATMs and savings banks characteristics are identified and followed from 1981 to 1998.[12] Sampling is affected by mergers and acquisitions taking place at the beginning of the 1990s that reduce the number of savings banks from 77 entities in 1986 to 50 in 1998. In order to dispose of the maximum number of observations for the estimation of the dynamic market potential model we have considered that merged savings banks are a sole entity from the beginning. Therefore, the data that refers to an entity affected by any of these processes will be equal to the arithmetic sum of the corresponding data of the savings banks integrated in the new firm.

The sample over which data is collected shares many common features with that described in Ingham and Thompson (1993) for the case of the UK. First, savings banks have been subject to tight regulation, which constrained important strategic variables. Although, deregulation in the last two decades is expected to have introduced a degree of heterogeneity, it provides us with an especially homogeneous sample over which to investigate the effect of firm-specific variables on internal diffusion. Second, the elimination of restrictions has produced an increase of competition between savings banks as they have been allowed to perform new activities, open new branches in new locations or use price as a strategic

[9] Survival models are frequently divided into parametric, semi-parametric and non-parametric for classification purposes. In this paper, we make use of a model included in the semiparametric group. The advantage of this model is that it does not make any assumption on the form of the underlying distribution.

[10] Note that the survival method is more demanding that the traditional approach in terms of the data required for the estimation, given that it uses longitudinal information on the explanatory variables.

[11] This is the period for which data on the number of ATMs installed in the savings banks is available.

[12] Savings banks characteristics are only available from 1986. All the other variables are available for the whole period.

variable. Furthermore, it has implied the recognition of commercial banks as close competitors and the interrelation between the two groups of financial intermediaries. This provides us with an excellent opportunity to analyse the influence of changes in market structure on the rate of internal diffusion.

To follow the first-step of the procedure outlined in Section 4.1, data on the cumulative number of adoptions and on the relevant variables affecting the maximum number of adopters is needed.[13] The key feature of the evolution of the market that justifies the use of a dynamic diffusion model is the increase in the number of branches. Prior to liberalisation, savings banks activities were geographically reduced in scope, with the largest operating within their autonomous regions and the smallest in one or two provinces. After the total lifting of entry regulation, the Spanish savings banks network substantially increased in size. Thus, from 1981 to 1998 the number of branches increases 80.6%, from 10,484 to 19,594. For the case of the ATMs, these figures are 169 and 20,244, respectively. In this situation, given that, with a few exceptions, ATMs are in-branch devices, the assumption of a static market potential seems unrealistic. This increase in the number of branches has been closely followed by an increase in the amount of total deposits of more than 100% in constant terms.

Therefore, the hypothesis is that the function specifying the maximum number of adopters $\bar{N}(t)$ takes the following form:

$$\bar{N}(t) = f[B(t)] = K_1 + K_2 B(t)$$

where K_1 and K_2 are parameters and $B(t)$ is the evolution of the total amount of deposits of the entity from adoption to 1998.[14]

Empirical work on the diffusion of innovations has traditionally been difficulted by the troublesome task of finding appropriate explanatory variables. Provided that the factors affecting the rate of diffusion (expected profitability, risk or learning) are rarely observable or measurable (Geroski, 2000), the literature on diffusion has attempted to overcome this problem through the utilization of proxies. Given that our case is not different, we use the same strategy. Therefore, the explanatory variables employed in the analysis heavily draw on the ones suggested by the literature on intrafirm diffusion.[15]

The profitability of the new technology (Hypothesis 1) is the first factor to consider. As it has been mentioned before, as a process innovation ATMs substitute labour. Hannan and McDowell (1984a) use the level of local market wage as the main proxy for this effect. In our case, firm labour expenditures are used under the hypothesis that differences among wages are found between entities and do not depend on the geographical area in which the operations of one savings bank take place (LABOU, labour expenditures normalised by assets).[16] Then, LABOU is expected to have a positive influence over the intrafirm rate of diffusion. A second variable, branch size, is also introduced. We should expect the profitability of installing ATMs to depend directly on branch size BSIZE (number of employees per branch[17]) due to the presence of fixed cost. This variable indicates the degree in which a savings bank's branches exceed the minimum size necessary to justify the introduction of an ATM (Levin et al., 1992). Therefore, we would expect to find a positive sign in the coefficient of this variable when the empirical analysis is performed.

The uncertainty surrounding the innovation (Hypothesis 2) is the second factor to consider. Uncertainty is expected to be reduced the longer the period

[13] As pointed out by an anonymous referee, the concept "maximum level of adoptions" may be confusing in our context, provided that we do not have information on an old technology which is substituted (and could be used as a benchmark). Nevertheless, given that ATMs are mainly located in branches the assumption is that there exists an upper limit on the number of maximum adoptions, which is estimated from the data.

[14] The relevance of other factors (number of branches, increase in the number of branches, increase in the number of deposits) at explaining the evolution of the potential market was also tested. The evolution of the total amount of deposits was the variable that performed better.

[15] A detailed description of the variables used in this research is presented in Appendix A.

[16] Given the absence of any information on the expected profitability of ATMs, several authors have proposed to use the potential for labour cost savings. Ideally, this variable should take into account only the information referring to the services for which ATMs are substitutes and should also reflect the evolution of the ratio ATMs to labour as the process of internal diffusion of the former evolves. This information is not available and, therefore, the results of the LABOU variable should be analysed with some care.

[17] The variable deposits per branch was also calculated in order to proxy for branch size. Given the high correlation of this variable with SIZE (0.97), it was not used in the empirical analysis.

the innovation has been used by other firms. Later adopters may be able to learn from other firms' previous experiences with the new technology, which would increase the benefits of later adoption. TIME is a variable representing the time elapsed between the year of introduction of ATMs in Spain and the year of first adoption by the firm. According to our second hypothesis, this variable should show a positive estimated coefficient, the longer the delay to adopt the innovation the quicker the intrafirm diffusion process.

Firm size, SIZE, is measured through total assets. Although, other proxies for firm size (number of employees, total deposits, ...) are available, they are not expected to show very different effects given the high correlation between them. According to Hypothesis 3, this variable should present a negative influence on the rate of intrafirm diffusion.[18]

As we have mentioned before, savings banks are mutual institutions. This character prevents them from obtaining funds from the traditional sources (e.g. the capital market) and limits the availability of financial resources to current profits and reserves. Therefore, the amount of total reserves (normalised by assets), LIQUI, is included in the analysis in order to proxy for liquidity effects. Similarly, the profitability of the entity, PROFI (return on assets), is also considered. Both variables have been suggested to have a positive effect on intrafirm diffusion (Hypothesis 4), as an indicator of the ability of a firm to finance the investment and to take risks (Mansfield, 1963).

Finally, market structure (Hypothesis 5) is captured through a weighted Herfindahl index, CONC. It considers the concentration in the local markets in which savings banks operate. To calculate it, a province Herfindahl index was first developed using the number of branches as a proxy for market share. Then, the core market Herfindahl was worked out multiplying each single Herfindahl of the provinces in which the entity was operating, by the relative importance of the province for the entity under observation. As we have seen, an inverse effect has been predicted. Therefore, a higher concentration should negatively influence the process of internal diffusion.

6. Results

The results of the estimation of the rates of intrafirm diffusion from expression (4) are generally satisfactory.[19] On average, the model was able to explain more than 98% of the variance of the dependent variable. From the 50 coefficients estimated, 47 presented the expected sign. As in Levin et al. (1992) no firm was omitted if the stage I model did not perform well.

Mansfield considers the time it takes a firm to complete the process of internal diffusion from 10 to 90% of potential market. Bearing these limits in mind, the number of years it takes a savings bank to complete the process of intrafirm diffusion ranges from 2 years for the quickest to more than 17 for the slowest. For the case of 11 entities the process is completed in a period of time no longer than 5 years. These figures are 24 for the entities that reach full internal diffusion in a period from 6 to 10 years and, finally, 12 entities take more that 10 years. A number of 37 entities out of a total of 47 whose potential market is available had finished the process of internal diffusion by 1998.

The 47 estimated *b* were used as the dependent variable in a second step in which the effect of the proposed variables on intrafirm diffusion was tested.[20] Table 3 presents the results of the estimation of several alternative specifications of the relationship between the *b* and the explanatory variables suggested by the literature on intrafirm diffusion. They are quite supportive. Overall, in all the cases the explanatory variables are able to explain more than 58% of the variance of the dependent variable, as measured by the adjusted R^2 statistic. This value is higher than the ones obtained in other empirical studies on intrafirm diffusion (Romeo, 1975; Globerman, 1976; Levin et al., 1992). As mentioned in Section 4 in all the

[18] As Geroski points out (2000), firm size is a variable frequently used in the literature on diffusion as a proxy for many influences that are not always mutually consistent. As argued before, in our case, this variable proxies for the absolute level of investment required to achieve a degree of internal diffusion and the speed of processes of decision-making.

[19] As it has been explained, to apply the first stage of the traditional procedure we need data on both the cumulative number of adoptions of ATMs, $N(t)$, and the evolution of the amount of deposits from 1981 to 1998, $B(t)$.

[20] Appendix B shows descriptive statistics on the explanatory variables used in this regression.

Table 2
Determining factors of the rate of intrafirm diffusion

Independent variables	(1) Estimated coefficient	(2) Estimated coefficient	(3) Estimated coefficient
CONSTANT	0.071 (0.154)	0.076 (1.513)	0.100** (2.349)
LABOU	0.690 (1.126)	0.317 (0.487)	
BSIZE	0.002* (1.772)	0.003* (1.838)	0.003** (2.306)
TIME	0.005*** (2.709)	0.005*** (2.776)	0.004** (2.292)
SIZE	−0.011*** (−3.197)	−0.012*** (−3.156)	−0.012*** (−3.473)
PROFI	0.002 (0.409)	−3.1E-04 (−0.058)	
LIQUI	0.409** (2.098)	0.375* (1.959)	0.330* (1.910)
CONC	−0.007 (−0.216)	0.285 (1.276)	
CONC2		−1.001 (−1.275)	
Adjusted R^2	0.5896	0.5890	0.6136
F-statistic	10.44***	9.24***	19.27***
Number of observations	47	47	47

* Statistical significance at 10% level. *T*-ratios in parenthesis.
** Statistical significance at 5% level.
*** Statistical significance at 1% level.

cases the OLS estimates have been corrected for heteroskedasticity using White's method (White, 1980).

The column (1) of Table 2 shows the estimation of a first model in which all the explanatory variables described in Section 4 have been included.[21] As has been mentioned, the statistics measuring the global goodness of fit are higher than the ones of other empirical analysis on intrafirm diffusion. From column (1) we may extract the following conclusions. Hypothesis 1 is partially confirmed. The ratio of labour expenditures to assets (LABOU) presents a positive and non-significant sign, indicating that cost saving issues are not relevant at explaining the rate of ATM diffusion. However, branch size (BSIZE) is shown to be a determining factor when explaining internal diffusion. Those entities with a higher average branch size are the quickest at introducing ATMs in their branches. The reduction of the uncertainty surrounding the innovation does provide savings banks with an incentive to adopt more units of the new technology in less time. The longer the time lag between the first introduction of ATMs in the market and the adoption of the technology by the savings bank (TIME) the quicker the diffusion among all its branches. Therefore, later adopters seem to have learned from previous adopters' experiences, confirming Hypothesis 2.[22]

Firm size is shown to have a negative and significant effect on the speed of intrafirm diffusion, confirming Hypothesis 3. Similarly to the findings of the literature on interfirm diffusion (Buzzachi et al., 1995) the logarithmic specification of firm size performed better. Therefore, the rate of intrafirm diffusion is shown to decrease with the amount of total assets, but this is achieved at a decreasing pace. The opposite happens with the amount of available resources to finance the acquisition of ATMs. The LIQUI variable presents a positive sign, indicating that those savings banks with more "retained earnings" are the ones that present a higher rate of internal diffusion, confirming Hypothesis 4. The profitability of the entity, however, is not shown to present any significant effect on the dependent variable.[23] Finally, the variable measuring

[21] All the values of the explanatory variables are taken as in 1986, given that this is the first year in which we have information on them. The only exception is the variable PROFI, for which an average value, 1986–1988, was calculated.

[22] As pointed out by one of the referees, TIME could also capture other effects as the influences of some variables that could not be inserted (price of the innovation, technological expectations or network externalities). Given the previsible existence of network externalities in ATMs, it is not implausible to think that the sign of the variable could be the consequence of "penguin and bandwagon effects" in the adoption and diffusion processes of the technology (Geroski, 2000; Choi, 1997).

[23] This result is consistent with the ones presented in Mansfield (1963) and Romeo (1975). In both cases, the profitability variable was found to be positive and no significantly related to the rate of intrafirm diffusion.

market concentration (Hypothesis 5) presents a negative and non-significant sign.

Given the non-significance of the variable capturing market concentration, column (2) attempts to further investigate its influence on the rate of intrafirm diffusion. As seen in Section 3, some authors point to the possibility that the relationship between market structure and innovative activity is quadratic. That is, this would imply that diffusion is maximised for intermediate levels of market concentration. Accordingly, column (2) presents new estimates in which this quadratic relationship has been specified. As shown, neither market concentration, nor its quadratic effect, presents a significant sign and global goodness of fit of the estimation is not significantly altered by the introduction of the quadratic effect.

Finally, the column (3) in Table 2 presents estimates resulting from the elimination of the variables that were never significant in the two previous estimations. In this case, all the variables introduced in the analysis present the expected sign. All of them are significant at the generally accepted levels and the global goodness of fit of the model is improved.

To further investigate the factors affecting the time elapsed from adoption to full internal diffusion, the Cox Proportional Hazards Model proposed in Section 4 was estimated.[24] The Efron (1977) approximation was used for handling ties. As in Mansfield (1963), the internal diffusion time was defined as the number of years from the acquisition of a number of ATMs equivalent from 10 to 90% of potential market.[25] The analysis is performed using the same as in the ordinary regression. The use of the time dimension of the data raises the number of available observations to 428. Note that the method allows us to relax the assumption that the explanatory variables remained constant throughout the diffusion period, used in the previous estimation.[26] The results of the estimation are shown in Table 3.[27] All three estimations are globally significant and present fairly stable coefficients. The estimated coefficients present some changes from the ones previously analysed.[28, 29]

The expected profitability of the innovation, as measured by the LABOU variable is shown to have a negative and highly significant effect on the conditional probability of having finished the internal diffusion process. These findings do not agree with the proposed hypothesis and the evidence brought forward by Hannan and McDowell (1984a,b) for the case of interfirm diffusion.[30] The effect of branch size is, again, positive and significant, confirming Hypothesis 1. Therefore, as branch size increases, the rate of intrafirm diffusion shows a higher value, pointing out the importance of fixed cost at using ATMs (Levin et al., 1992).

The time lag of adoption of the innovation does have a negative effect (positive coefficient) on the time from adoption to full internal diffusion, as hypothesised. This, again, confirms the importance of uncertainty at explaining the speed of intrafirm diffusion. Firm size is shown to have a negative effect on the probability of having reached 90% diffusion.[31]

[24] Appendix C shows descriptive statistics for the variables used in the survival analysis.

[25] To estimate these thresholds we used the results obtained in the first stage of the traditional method, which have been previously analysed in Section 6.

[26] This is, in fact, one of the criticisms of Stoneman (1983) to the model developed by Mansfield (1963). Mansfield assumes size, liquidity and the expected profitability of the innovation to remain constant over time.

[27] We also estimated a robust variance survival model. The conclusions commented here are not affected by the results.

[28] This difference in results should not be surprising, given that, as commented in the main text the estimations of the survival model make use of the longitudinal dimension of the data. This is a clear advantage when dessaggregated information on the process of internal diffusion is available.

[29] Note that in the case of the survival estimation, the baseline hazard captures the effect of time after having introduced the explanatory variables in the model. Given that we do not include supply side factors, the baseline hazard reflects, at least in part, the impact of such factors (Sharma, 1993).

[30] In Maudos (1994) the intensity of use of the ATMs in the Spanish savings banks is studied. Contrary to hypotheses, he also obtains a negative (although significant at the 86% level) coefficient for the LABOU variable measured as labour expenditures per employee. In any case, this result should be taken with some care. As commented before, the availability of data does not allow to control for the ratio ATMs to labour for the services in which they are substitutes. If the substitution assumption holds true, the process of internal diffusion of ATMs should produce a decrease of the value of the LABOU variable (a reduction in employee expenditures, ceteris paribus), explaining the negative and significant coefficient.

[31] Given the high correlation between the natural logarithm of firm size and time (0.52) this transformation was not used in this case.

Table 3
Survival analysis of the determinants of intrafirm diffusion

Independent variables	(1) Estimated coefficient	(2) Estimated coefficient	(3) Estimated coefficient
LABOU	−0.149*** (−2.834)	−0.141*** (−2.801)	−0.144*** (−2.89)
BSIZE	0.377** (2.365)	0.356** (2.303)	0.355** (2.31)
TIME	0.436*** (3.237)	0.437*** (3.212)	0.454*** (3.49)
SIZE	−0.725* (−1.788)	−0.626* (−1.786)	−0.619* (−1.79)
PROFI	−0.254 (−0.523)		
LIQUI	6.823 (0.639)	3.913 (0.422)	
CONC	−7.722* (−1.825)	−7.863* (−1.832)	−7.934* (−1.87)
Likelihood ratio	20.3***	20***	19.8***
Number of observations	428	428	428

*** Statistical significance at 1% level.
** Statistical significance at 5% level.
* Statistical significance at 10% level. *T*-ratios in parenthesis.

Neither of the two variables measuring the availability of financial resources is, however, significant. Perhaps the most interesting findings of this second estimation are that, when the evolution of market structure during the period under analysis is taken into account, the influence of market concentration on the rate of intrafirm diffusion is shown to be negative and significant. This evidence is consistent with that presented in Levin et al. (1992) and clearly rejects the link between market structure and innovation activity suggested by the Schumpeterian hypothesis, providing us with interesting conclusions regarding the transformations that have affected the market following liberalisation. Intrafirm diffusion seems to have been favoured by the changes that have affected the market and reduced the concentration levels, as measured by the Herfindahl Index. In this sense, perhaps the most beneficial effect has to be associated to the entry processes derived from the elimination of branching restrictions.

Table 4 presents the result of exponentiation of the values of the coefficients of the variables that were significant in the survival analysis.

Table 4
Change in the hazard of a 1 S.D. change in the covariates

Independent variables	Exponentiated coefficient	Change in the hazard
LABOU	0.865	0.522
BSIZE	1.425	1.638
TIME	1.574	1.960
SIZE	0.538	0.622
CONC	3.58E−04	0.689

The interpretation of the coefficients is analogous to the classical regression. For example, for the case of the variable TIME, an additional year of delay in the adoption of ATMs increases the hazard of having reached full internal diffusion by 1.574. In the same way, an increase in a standard typical deviation in this variable implies that the conditional probability of having completed 90% of the potential market almost doubles (1.960). In the case of the concentration variable, this conditional probability is multiplied by 0.689.

7. Conclusions

This paper investigates the factors explaining the intrafirm speed of diffusion of a new technology, the ATM, in the Spanish savings banks through the use of a dynamic diffusion model. The analysis of this dimension of the diffusion process has been largely neglected by both the theoretical and the empirical literature on technological progress. The relevance of covering this gap in the literature is explained by two important factors. First, new technology is frequently divisible and provided in a large number of small units, rendering the initial adoption as only a first step in the wider diffusion process. This is, in fact, the case of the ATMs. As we have seen, at the end of the observation window time of our empirical analysis, the number of units introduced by the savings banks was well over 21,000. Second, its importance increases due to the fact that a great deal of the internal diffusion process takes place among a population of big firms. This is, again, the case of the Spanish savings banks in which intrafirm diffusion takes place among a sample of 50 entities, with the three largest accounting for more than 44% of the installed machines (9628 units).

As pointed out by Mansfield (1963), the analysis performed confirms that interfirm and intrafirm diffusion processes share common features. However, there are also some distinguishing characteristics. Following previous research, innovation, firm and market specific factors have been included in the analysis.

The results are satisfactory in terms of the support received by the hypothesis proposed. The application of the regression and survival methods over the data suggests that the influence of firm size and market structure on the rate of intrafirm diffusion are clearly not Schumpeterian. Firm size is shown to have a negative effect on the rate of intrafirm diffusion. These findings agree with previous research that indicates that smaller firms are quicker in decision processes and need a lower amount of total investment to fully adopt the innovation. However, it points in the opposite direction to interfirm studies, in which the influence is found to be positive. In the same way, the relation between market concentration and intrafirm diffusion has been found to be negative. Internal diffusion seems to be quicker the lower the level of concentration in the market, confirming the hypothesis proposed by Mansfield. This result adds new evidence on the conflicting effects of market structure on innovation and diffusion presented in the literature. It also suggests that entry and the subsequent increase in rivalry that has taken place in the geographical markets in which the savings banks operate have been beneficial from the point of view of dynamic efficiency.

The testing of the hypothesis concerning the expected profitability of the innovation offers inconclusive results. Whereas, it shows that higher labour expenditures do not have the predicted effect on the rate of diffusion, it also highlights the importance of fixed costs and minimum branch size over intrafirm diffusion. Savings bank profitability has been shown not to have any effect over the rate of intrafirm diffusion. Although, this does not support the hypothesis developed, it is in agreement with other studies with the same objectives (Mansfield, 1963; Romeo, 1975). Finally, contrary to the literature on interfirm diffusion, an attempt has been made to distinguish between the effects of size and liquidity with the introduction of a variable measuring the latter. The results show that liquidity does have a positive and significant effect on the rate of internal diffusion, as expected.

The last factor that explains the rate at which savings banks have proceeded with the diffusion process is the time lag of adoption (time from first adoption in the industry). As pointed out in the main text, the later the adoption time the quicker the diffusion process. Thus, later adopters may have benefited from the experience accumulated on the new technology by other entities. As argued by Pindyck (1991), the option of waiting may have a great value if there is important information to arrive and strategic factors do not compel the savings banks to quickly go forward in the diffusion process. The result highlights the role of the uncertainty associated with the innovation when explaining investment in new technologies.

The empirical analysis has been performed making use of survival or duration models. These models take the time to an event as the dependent variable in the analysis. Although, they had been applied to the analysis of interfirm diffusion, no attempt had been made to use this type of models in the study of the speed at which innovations diffuse in the firm. As we have argued, the application of these models to the study of intrafirm diffusion should be given serious consideration provided their advantages to traditional methods. This is especially the case when longitudinal information is available on the process of internal diffusion. Nevertheless, hazard models that do not assume any underlying distribution (as the one used in this paper) are also an interesting tool to explore alternative forms to the S-shaped curve omnipresent in diffusion studies.

Some limitations and extensions derive from our research. In relation to the first, the main ones are related to the assumptions underlying the fundamental diffusion model. In our context, perhaps the most relevant is the one that assumes that the technology does not change during the diffusion process and that it is independent of other innovations. Given the long time period elapsed from first introduction of ATMs and the speed at which information technologies have evolved and have been applied to banking in the recent years, this may be unrealistic. It is also worth highlighting the difficulty to find appropriate proxies for measuring concepts, such as expected profitability or uncertainty. Its unmeasurable and unobservable character turn the interpretation of empirical results into a troublesome task.

In relation to the second, given the developments in the Spanish banking sector, the analysis could be extended in order to disentangle the effects of strategic factors over the rates of intrafirm diffusion. These effects have been, in fact, already considered in the interfirm diffusion literature. Thus, Hannan and McDowell (1986) and Sharma (1993) test the influence of rival precedence in the adoption of ATMs in the US banking market. As they point out, the theory has yielded ambiguous predictions on the impact of this factor over the probability of adoption. Whereas, rival precedence may reduce uncertainty about the profitability of the innovation, it also reduces this profitability due to the provision of a higher quality of service. The influence of strategic factors, such as the ones studied in these two papers has not been undertaken in the intrafirm dimension and could constitute a next step in future research.

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Appendix A. Definition of variables

Hypothesis	Variables
H1: expected profitability	LABOU: total labour expenditures divided by total assets. Data on this variable is available from 1986 to 1998.
	BSIZE: total number of employees divided by the number of branches. Data on this variable is available for 1986.
H2: uncertainty	TIME: time elapsed between the adoption of ATMs by the first firm in the market and the firm under analysis.
H3: size	SIZE: total assets. Data on this variable is available from 1986 to 1998.
H4: liquidity	LIQUI: equity divided by total assets. Equity includes capital, rotation fund, reserves, subordinated financing and retained earnings. Data on this variable is available from 1986 to 1998.
	PROFI: net profit divided by total assets. Data on this variable is available from 1986 to 1998.
H5: market structure	CONC: overall Herfindahl Index in the provinces in which the entity is operating. This index was calculated as follows. A province Herfindahl was first developed using the number of branches as a proxy for market share. Then, the core market Herfindahl was worked out multiplying each single Herfindahl of the provinces in which the entity was operating in the corresponding year, by the relative importance of the province for the entity under observation (the number of branches was again used to measure the importance of the province for the entity). Data on this variable is available from 1986 to 1998 and has been calculated taking into account both types of intermediaries, banks and savings banks.

Appendix B. Regression analysis of intrafirm diffusion

Descriptive statistics

	LAB	BSIZE	TIME	SIZE	PROFI	LIQ	CONC
Minimum	0.011	2.453	4.000	3686	0.031	0.016	0.062
Mean	0.020	5.518	5.809	260143	1.187	0.046	0.127
Maximum	0.028	8.991	10.000	2604568	2.076	0.095	0.268
Total *N*	47	47	47	47	47	47	47
S.D.	0.004	1.388	1.715	422133	0.459	0.015	0.048

Correlation between the variables

	LAB	BSIZE	TIME	SIZE	PROFI	LIQ	CONC
LAB	1.000						
BSIZE	0.195	1.000					
TIME	−0.027	−0.246	1.000				
SIZE	−0.190	0.247	−0.267	1.000			
PROFI	−0.392	−0.004	0.162	−0.395	1.000		
LIQ	−0.441	0.039	0.253	0.113	0.364	1.000	
CONC	0.046	−0.042	−0.218	−0.106	0.171	−0.022	1.000

Appendix C. Survival analysis of intrafirm diffusion

Descriptive statistics

	LAB	BSIZE	TIME	SIZE	PROFI	LIQUI	CONC
Minimum	0.527	2.453	4.000	0.004	0.031	0.015	0.062
Mean	18.697	5.460	5.530	0.398	1.164	0.064	0.141
Maximum	30.051	8.991	10.000	5.331	2.076	0.145	0.347
Total *N*	428	428	428	428	428	428	428
S.D.	4.516	1.390	1.483	0.768	0.457	0.026	0.047

Correlations between the variables

	LAB	BSIZE	TIME	SIZE	PROFI	LIQUI	CONC
LAB	1.000						
BSIZE	0.247	1.000					
TIME	0.229	−0.228	1.000				
SIZE	−0.301	0.202	−0.175	1.000			
PROFI	−0.259	−0.037	0.053	−0.393	1.000		
LIQUI	−0.301	−0.095	0.048	0.141	0.217	1.000	
CONC	−0.168	−0.179	−0.142	−0.024	0.116	0.121	1.000

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