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The endogenous relationship between innovation and diversification, and the impact of technological resources on the form of diversification

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Abstract

This research has endeavoured to build on earlier research on the relationship between a firm's technological resources and the direction of its diversification, by trying to confirm the endogeneity of this relationship and by addressing the influence of innovation on the choice of the mode of diversification. Based on a sample of Spanish firms, our results suggest that innovation drives diversification, but not the reverse. The second important finding of this research is the empirical confirmation that knowledge assets are not related to the diversification mode.

Keywords: R&D strategy; Technological assets; Patents; Europe; Growth

1. Introduction

The relationship between diversification and innovation in business corporations has long been a focus of research. Research on this topic indicates that there is a relationship between innovation and the direction of diversification (Jaffe, 1986; Baysinger and Hoskisson, 1989; Cantwell and Bachmann, 1998; Silverman, 1999; Silverman, 2002; Miller, 2004) though other studies also suggested that diversification strategy was driving investment decisions in R&D. The coexistence of these two relationships raises the possibility of the potential existence of a bidirectional relationship between innovation and diversification. According to Shaver (1998), the diversification decision process is endogenous and self-selected. Shaver goes on to argue that empirical models that do not take into account the endogeneity of this process are potentially mis-specified.

Nevertheless, most studies of the relationship between diversification and innovation assume that the relationship has one, specific direction, either focusing on the impact of innovation on diversification, or on the impact of diversification on innovation. We have not found any research paper suggesting a potential bidirectional relationship between innovation and diver-

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sification. Hence, the first contribution of this paper will be to jointly consider both directions of this relationship and perform a check for endogeneity on innovation and diversification.

The literature on diversification identifies some of the factors explaining the mode of diversification such as the organizational form of the firm (Pitts, 1980), the industry entry barriers (Yip, 1982) or the level of financial resources of the firm (Kochhar and Hitt, 1998). However, earlier studies of the relationship between diversification and innovation were limited to a consideration of the impact of innovation on direct diversification, neglecting the impact of innovation on indirect diversification. Inevitably, those works did underestimate the impact of innovation on diversification. Recently, Silverman (2002) went one step further and considered the impact of the applicability of the pool of technological resources of a firm on its diversification mode decision. However, the empirical results of this research were not conclusive as he found a modest but significant relationship between internal expansion and the applicability of technological resources for only a subsample of technology-intensive firms. Moreover, this research only studied a sample of large US firms, and the data was more than 20 years old. For these reasons, the second relevant contribution of our research is the analysis of the relationship between knowledge assets and the mode of diversification using a sample of Spanish firms of varying size, and with more recent data.

The rest of the paper is organized as follows: in Section 2 we review the theoretical and empirical research on the relationship between the technological intangible assets of a company and diversification; in Section 3 we describe the data sources and the specification of the model; in Section 4 we present and discuss the results of the empirical research; finally in Section 5 we present the main conclusions of the paper.

2. Innovation and diversification: a bidirectional relationship

Since 1959 when Nelson studied the relationship between basic research and diversification strategy, a great deal of research has been devoted to analysing the relationship between innovation and diversification in business. It is possible to identify in this literature an initial stream of research focusing on the impact of the direction of innovation on a firm's diversification strategy. Most arguments presented from this perspective can be summarized by Miller's argument (2004) to the effect that strategic theory implies that firms with superior technological resources may diversify to gain economies of scope in knowledge assets. MacDonald (1985) found that firms diversify in order to transfer intangible organisational capital.

A similar argument was also supported by some case studies (Suzuki, 1993), where diversification was not the result of the maturity of some markets, but the natural consequence of employing technological innovation capabilities to expand into related markets. In the same line of thinking, Silverman (1999) observed that firms are more likely to diversify into those businesses where their technological resources have wider applicability. From the perspective of the Resources Based View literature, more innovative firms developed greater capabilities (Dierickx et al., 1989), which could be used by the firms to enter new markets (Cohen and Levinthal, 1990; March, 1991; Nonaka and Takeuchi, 1995; Teece et al., 1997; Hargadon and Sutton, 2000).

Transaction Cost Theory also supports the positive relationship between innovation and the direction of diversification, explained by the fact that firms that developed new knowledge through R&D activities are more likely to enter new markets to exploit that new knowledge when viable contractual alternatives to do so do not exist (Silverman, 1999). Along the same lines as this argument, Arrow (1962) suggested that the results of basic research may have commercial value only for the firm that conducted that research. In consequence, firms must enter new industries in order to enlarge the range of applications and increase the profits derived from the new knowledge (MacDonald, 1985).

Finally, more recent theories such as the knowledge-based theory (KBT) also support this view and consider that the strategy of internal diversification of a company may be explained in terms of branching-out from its existing knowledge and key competences (Nonaka, 1991; Nonaka and Takeuchi, 1995). Recent research (Bresci et al., 2003; Camelo-Ordaz et al., 2004) followed the line of argument presented by Kim and Kogut (1996) that knowledge-relatedness is a key factor in affecting the technological diversification of firms, and therefore developing and investing in knowledge and related capabilities enables companies to undertake processes of diversification. We must also point out that some other papers argued that there was a negative relationship between innovation levels and diversification. Hall (1990) demonstrated that firms with lower levels of R&D investment were more likely to diversify than more innovative firms. Miller (2004) confirmed that prior to the diversification event, diversifying firms have lower R&D intensity than non-diversifying firms in the same industry. One possible explanation of this result is that firms that lag behind in

R&D outnumber firms that are ahead of the field in R&D.

As remarked upon in the introduction, a second stream of research reported a causal link between diversification strategy and innovation levels. Scherer (1965) found a positive association between diversification and R&D expenditures at different levels of industrial aggregation, using both four and five digit SIC codes. In a similar vein, Scott and Pascoe (1987) have shown that R&D expenditures depend on a firm's diversification pattern. Hitt et al. (1988) argued that diversification strategies may discourage risky decisions such as long-term investments in R&D. Hoskisson and Johnson (1992) noted that higher acquisition intensity is associated with less internal innovation. Rogers (2002) described how more focused firms tend to have higher R&D intensities. Finally, Penner-Hahn and Shaver (2005) observed that in the pharmaceutical industry, international diversification and innovative effort were positively related.

From the paragraphs above, we can draw the conclusion that the literature suggests the existence of a positive relationship between innovation relatedness and diversification, but at the same time diversification strategy has some influence on investments in R&D. The existence of both relationships casts some doubt on the potential existence of endogeneity between innovation and diversification decisions. Shaver (1998) already suggested this possibility, but did not provide empirical evidence for the suggestion. The interest in solving the endogeneity problem between innovation and diversification was reinforced by Miller (2004). He did not study the endogeneity between innovation and diversification, but the endogeneous effects of diversification and performance. However, he suggested that technological resources played some role in this endogeneous relationship. In spite of this intimation of endogeneity between innovation and diversification decisions, we did not find any research specifically incorporating an endogeneity check aimed at confirming the bidirectional relationship. This gap in the literature will be the basis for our first proposition:

Proposition 1. *There is an endogenous relationship between the direction of innovation and the direction of diversification.*

We believe that confirmation of this first proposition will contribute significantly to the field. If our first proposition is true, that would imply that the specific direction of the relationship will depend on the multiplicity of factors affecting the firms or the markets where they operate. A vast new field of research could develop, exploring which factors explain the direction of the relationship.

3. Innovation and the form of diversification

Our second research question was related to the relationship between innovation and the form of diversification. In other words, we wanted to ascertain whether knowledge assets were taken into account when firms choose between internal growth and acquisitions.

Some literature suggests that there is a positive causal link between innovation and internal development. The argument supporting this positive relationship is that internal growth is the most efficient way to transfer knowledge to the subsidiary because it offers less risk in terms of organizational control than acquisitions (Hennart and Park, 1993), it favours organizational learning (Kogut and Zander, 1992) and it limits the problems of misappropriation of the knowledge, thus preventing opportunism (Williamson, 1991) and loss of competitive advantage (Barney, 1991). Some initial evidence supports the positive relationship between innovation and direct diversification: Tsai and Cheng (2004) showed that more R&D intensive Taiwanese firms have a higher likelihood of foreign expansion through wholly owned subsidiaries, Hennart (1991) observed that Japanese firms who establish U.S. affiliates to exploit their proprietary know-how will want to keep full control of their subsidiary, while Silverman (2002) found for a subsample of technology-intensive firms that the greater the technological resources required to enter an industry, the greater the likelihood of internal expansion. Blonigen and Taylor (2000) found that low R&D-intensity firms were more likely to acquire.

The other side to the positive relationship between innovation and internal diversification is the relationship between scarcity of knowledge resources and acquisitions. In effect, acquisitions could substitute for innovation (Hitt et al., 1990; Karim and Mitchell, 2000) and through them firms would obtain resources that were difficult to develop internally (Miller, 2004). Thus, innovative firms will be more likely to diversify through internal development to keep organizational control and to protect their knowledge assets, while R&D laggards would opt for indirect diversification.

Proposition 2a. *There is a positive causal relationship between innovation and the direction of diversification through internal development*.

Despite the empirical evidence discussed above, we had some doubts on the positive relationship between innovation and direct diversification. These doubts stem from three arguments. First, some research found that knowledge based resources were not specific to either internal or acquisitive modes of expansion (Chatterjee and Singh, 1999). Second, the existing evidence supporting the positive relationship between high levels of innovation and internal diversification applies to very specific research frameworks. The empirical evidence of Silverman (2002) applies only to technology-intensive firms with patent portfolios of more than 50 patents, Blonigen and Taylor (2000) only studied High Technology Industries, and Ruckman (2005) demonstrated that the relationship between R&D and mode of expansion is different depending on the nationality of the acquirer. She observed that foreign acquirers with low R&D intensity choose targets with high R&D intensities, which suggests technology sourcing as a motivation, while domestic acquirers prefer targets with high R&D intensities the higher their own R&D intensity, which suggests synergy as a motivation. Thus the results from Tsai and Cheng (2004) or Hennart (1991) may be biased as they only considered the diversification decision of foreign acquirers. Third, firms use diversification by acquisition to access resources and capabilities complementary to their technological knowledge, such as market knowledge, brands, managerial expertise or even some other technological knowledge that could complement the patents of the acquiring firm. For these three reasons, we think that we may expect that some innovative firms also use acquisitions to enter new markets.

Proposition 2b. *There is a positive causal relationship between innovation direction and the direction of indirect diversification.*

3.1. The model

Lemelin (1982) put forward an analysis of decisions made by firms to diversify, suggesting that this was determined by the firm' specific resources, the characteristics of the target industry and the differences between the target industry and the industry where the firm is currently operating. We will follow this approach, which can be operationalized as follows (MacDonald, 1985; Merino and Rodríguez, 1997):

$$D_{ik} = f(\mathbf{X}_i, \mathbf{W}_k, \mathbf{Z}_{ik})$$

D_{ik} is a measure of the diversification of the firm i to the target industry k. $\mathbf{X}_i$ is a vector of the specific characteristics of the firm; in the case of the present study it will be a measure of the stock of intangible, technological assets held by the firm. $\mathbf{W}_k$ is a vector of the characteristics of the target industry, and $\mathbf{Z}_{ik}$ is a vector related to the differences between the target and the source industry.

Due to the data available, instead of using simultaneous equations we will use instrumental variables to check the endogeneity hypothesis. Our focus is not conceptually new as it is very similar to the model proposed by Shaver (1998), who also used a latent (unobservable) variable approach. The difference between our approach and that of Shaver is that we adapted that framework to the econometric requirements of our model with a dichotomous variable measuring diversification and a count variable measuring the technological resources of the firm. In the following sections we will describe the sample, the variable measures, and the econometric specification of the model.

3.2. The sample

The sample consisted of industrial firms with at least one employee. The only service industry we included in our sample was the telecommunication industry because of its economic relevance and intensity of innovation. We excluded the rest of the service industries because of the problems related to the definition and measurement of innovation within those industries (INE, 1999, p. 21).

The sample was obtained from the INFOTEL database. This database is managed and updated by the Spanish firm Axesor-Grupo Infotel. The Infotel data includes official book records such as profit and loss accounts, balance sheet information, stakeholders and board of directors, subsidiaries and financial ratios. We used INFOTEL to obtain the name of the firm, the yearly CNAE codes (the Spanish equivalent for the US SIC codes), the revenues and profits for the period 1990–1999, and the R&D expenditures for the period 1995–1999. Information on R&D expenditures before 1995 was very incomplete. As we will note later, we supplemented this data with information from some other databases such as SABI,[2] INE[3] and the European Patent Office.

To construct a robust sample, we selected only firms who declared that they had invested in R&D in at least three of the years between 1995 and 2000. Following Silverman's (1999) methodology, a random sample was extracted from this subset. The sample was reduced to

[2] Sistema de Análisis de Balances Ibéricos (SABI) is another database of official book records for Spanish firms.

[3] Instituto Nacional de Estadística (INE) is the Spanish Statistical Institute.

Table 1
Sample structure by industries (CNAE 93)

Industry	Firms
10 Coal mining	12
11 Oil and gas extraction	5
13 Metal mining	5
14 Mining and quarrying of non-metallic minerals, except fuels	18
15 Food products	112
17 Textile mill products	42
18 Apparel and leather	10
19 Leather accessories	11
20 Lumber and wood products, except furniture	14
21 Paper and allied products	25
22 Printing, publishing and allied industries	32
23 Petroleum refining and related industries	8
24 Chemicals and allied products	108
25 Rubber and miscellaneous plastics products	57
26 Non metallic mineral products	61
27 Primary metal industries	35
28 Fabricated metal products, except machinery and computer equipment	65
29 Industrial machinery	89
30 Commercial and computer equipment	9
31 Electrical equipment and components	50
32 Electronic equipment and components	31
33 Measuring, analyzing and controlling instruments	16
34 Motor vehicles and motor vehicle equipment	67
35 Other transportation equipment	26
36 Furniture and miscellaneous manufacturing industries	31
37 Recycling industries	4
40 Electricity, gas, steam and hot water production and distribution	15
41 Water supply and sanitary systems	10
64 Communications	15
Total	983

take account of some missing data,[4] and the final sample consisted of 983 firms. This size represented a standard error of 1.6% ($p=q$) for the 1999 population we considered in our study. We found higher standard errors for some industries. Table 1 describes the final sample structure.

3.2.1. Dependent variable

In line with Silverman (1999), we took the entry of existing firms into new CNAE codes during the 2-year window 2000–2001 to be a function of the firm and industry characteristics during the period 1990–1999. Although it would be desirable to study a more recent time period, focusing on the 1990–2001 period allowed us to integrate information from multiple sources.

Our dependent variable will be the diversification strategy, coded as a categorical variable. As noted above, we considered in our study the relationship of innovation with both direct and indirect diversification. In terms of our research, indirect diversification occurs when the firm i moves into some new CNAE code by purchasing a majority stake in a firm operating in that industry. Because of the scarcity of data available for Spanish firms at the four-digit level, we were forced to consider the industry at the two-digit level. Conceptually, this limitation in effect restricted our research to the study of the decision to diversify into unrelated areas. However, the study of the distinction between related and unrelated diversification was outside the scope of this research.

To test our first proposition, the diversification decision was represented by a dichotomous variable, D_{ijk}, which became one when the firm i decided to enter industry k during the period 2000–2001, and zero otherwise. The variable D_{ijk} did not take into account the specific characteristics of the industries where our sample firms may be present. For instance, we treated in an identical manner two different firms, one operating in the household furniture industry and entering the electronics industry and another firm also operating in the household furniture industry but diversifying into the woodworking machinery industry.

The variable D_{ijk} measures the diversification *direction*, telling us whether a firm diversified or not. We will try to clarify this concept by an example. Supposing that the firm $i=1$ is operating in the industry $j=2$ and decides to move into industries $k=3$ and $k=4$, then we will have $D_{123}=1$ and $D_{124}=1$. There are 56,025 possible instances of D_{ijk}[5]: in 875 of those cases D_{ijk} took the value 1. That is to say, in our sample firms made 875 positive decisions to enter new industries during the year 2000–2001. Moreover, in our sample 487 firms (49.54% of the sample) decided to diversify, while 496 firms did not enter a new industry during the 2000–2001 period. D_{ijk} was also intended to measure the diversification intensity of a firm, being measured by the number of

[4] One of the problems of defining the sample was that some firms with data for the period 1990–1999 disappeared during the period 2000–2001.

[5] We defined the potential diversification cases as follows: from the 60 industry categories at two digit CNAE 93 level, we excluded code 95 (homes employing employees). The number of potential diversification cases was then 983 firms × 59 industries at two digits CNAE 93 level − (983 industries of origin + 989 industries in which firm i participates before 2000) = 56025 cases.

industries for that firm. The firms in our sample entered a number of industries ranging from 1 to 13, and the average firm diversified into 1.7 industries, or almost 2 industries, during the period 2000–2001.

To test our second proposition, the diversification mode choice was represented by a dichotomous variable (DIRECT_{ik}) for the firm i and the industry k. This variable became one for direct diversification, and zero for indirect diversification. We identified 328 cases of internal development and 547 cases of external development.

3.2.2. Innovation variable

The technological innovation process may be studied from two different but complementary points of view: the input side and the output side. The input side studies the sources and determinants of the technological innovation process. The output side analyzes the results of the technological innovation process in terms of the development of commercial applications. If the researcher pays more attention to the input side, the implicit assumption is that there is a proportional relationship between the R&D input and the output (OCDE, 1981, p. 82). Nevertheless, the input side analysis does not explain the direct result of the scientific and technological efforts and does not consider the impact of the innovation process on the firm's strategy.

For these two reasons, we decided to adopt the output side approach and to use patents to measure the innovation process. A first reason to adopt patents was that they were deposited, examined, safeguarded and published by specialized institutions, which guarantee the novelty and relevance requirements of an invention. Another reason for using patents is that patent information is, in general, easily available. Another advantage of patents is that they are an appropriate measure of technological change when R&D data is not available (Pakes et al., 1988). A final advantage of using patents is that they are assets that can be exploited, rented or sold.

There are also some problems relating to patents. First, not all inventions are patented. Consequently, choosing patents to measure the stock of intangible assets can underestimate this stock. Second, patenting behaviour varies from industry to industry (Wright, 1999). Another problem with patents is that, as we know from the Frascati Manual (OCDE, 1981), patents were created to protect intellectual property rights and not to measure the output of the innovation process. For this reason, we needed to adapt the *International Patent Classification* (IPC) to the CNAE 93 industrial activity classification.

The variable PAT_{ik} measured the output of the innovation process. This variable is the result of counting[6] the patents that the firm i received in the industry k during the period 1995–1999 from the European Patent Office.[7]

3.2.3. Control variables

The control variables we introduced in our model were defined according to the Lemelin (1982) model. We first present the group of control variables related to the target industry, and then we will explain the control variables related to the firm.

Among the control variables that related to the industry, for the period 1990 to 1999, we first considered the variable OUTPUT DIFFERENCE (ODIF_{ki}) which was defined as the difference between the average output growth rate of the industry k (O_k) and the average output growth rate of the firm i (O_i). We would anticipate that firms with lower output growth rates would enter industries with higher output growth rates. If ODIF_{ki} was positive, the diversification likelihood will be higher, while negative values of ODIF_{ki} implied lower likelihood of diversification. We used the Infotel and SABI data to calculate the output growth rates of the firms and the INE database information to compute the industry's growth rates.

Secondly, we allowed for the difference between the average profits (after taxes) of the firms in the target industry k and the profit of the firm i. This difference was represented by the variable PROFIT DIFFERENCE (PDIF_{ki}). We would expect that firms with lower profits and hence with higher values of PDIF_{ki} will be more likely to diversify. Data sources for PDIF_{ki} were the same as for ODIF_{ki}.

We also allowed for the industry entry barriers. We first measured the barriers to entry using the industry concentration. We then defined the variable INDUSTRY CONCENTRATION ($\mathrm{CR4}_k$) measuring the CR4 index for industry k in 1999. We would anticipate that higher concentration values would imply lower likelihood of diversification. We constructed the concentration ratios using the SABI database information.

[6] The process we followed to count patents was: for each firm in the sample, we looked for the patents that it had in the EPO's database. For each patent, in turn, we looked for the IPC code assigned by the EPO. The IPC codes describe the potential economic uses for that patent. We then matched the IPC code with the Spanish CNAE codes. When the information available was not enough to undoubtedly assign a patent to a particular CNAE code, we contacted the firm to ask them in what CNAE code were they using the patent. For instance the IPC code D21 PAPER MAKING, PRODUCTION OF CELLULOSE corresponded to the CNAE Code 21 PAPER INDUSTRY.

[7] Available at http://www.oepm.es.

We also measured the barriers to entry taking into account the variable INDUSTRY R&D (R_k) defined as the average R&D expenditure level in the target industry during the period 1990–1999. We anticipated that industries with higher R&D levels would have higher entry barriers. We defined the R_k variable using the INE database information.

Another proxy for entry barriers was the variable RDIF_{ik} that measured the difference between the R&D intensity of the firm and the R&D intensity of the target industry. The argument behind this control variable is that firms will be more likely to enter industries with similar R&D intensity (Merino and Rodríguez, 1997). RDIF_{ik} is computed by the product of two differences $(R_i - R)$ and $(R_k - R)$, R being the average R&D expenditure level for all the firms in our sample, R_i the average R&D expenditure level for the firm i, and R_k the average expenditure level for the firms in the target industry k during the period 1995–1999. High positive values for RDIF_{ik} implied similar R&D expenditure levels for the firm i and the industry k, while low or negative values implied different R&D intensities.[8] Therefore, high positive values for RDIF_{ik} are linked to higher likelihood of diversification. Information to calculate this variable was obtained from the Infotel and INE databases.

The last control variable in our model was the size of the firm. It is widely agreed that diversification is a natural evolution in the growth of a firm, firstly because we would expect new investment opportunities to be exploited through the diversification of established firms, rather than by the action of new entrants (Grant and Jammine, 1988), secondly because intensively diversified firms tend to be bigger than less diversified firms (Christensen and Montgomery, 1981; Aw and Batra, 1998), thirdly because size is a proxy for the financing capabilities of the firm (Nathanson and Cassano, 1982) and fourthly and finally because smaller firms tend to have some organizational deficiencies, which also impede diversification. Consequently, and *a priori*, firm size and profitability will have a positive influence on diversification. In order to allow for firm size, we will use both the logarithm of the average revenues (LOGREV_i) and the logarithm of the average profits after taxes (LOGPROFIT_i) for the period 1990–1999. We constructed these variables using information from the Infotel and SABI databases.

3.3. Econometric model

In terms of Lemelin's (1982) model and using the notation employed in the section above, the vector of the firm's characteristics ($\mathbf{X}_i$) included variables PAT_{ik}, LOGREV_i and LOGPROFIT_i; the vector of the target industry ($\mathbf{W}_k$) is formed by the variables CR4_k and R_k; and the vector of the similarities between firm i and industry k ($\mathbf{Z}_{ik}$) includes variables RDIF_{ik}, ODIF_{ki}, and PDIF_{ki}. Table 2 summarizes the variables defined in our model, and the main data sources employed in their construction.

Once we have defined the variables, we specify our econometric models:

$$\begin{aligned} &P(\text{DIVERSIFICATION} = 1) \\ &\quad = \beta_0 + \beta_1\,\text{PAT}_{ik} + \beta_2\,\text{LOGREV}_i \\ &\qquad + \beta_3\,\text{LOGPROFIT}_i + \beta_4\,\text{CR4}_k + \beta_5 \text{R}_k \\ &\qquad + \beta_6\,\text{RDIF}_{ik} + \beta_7\,\text{ODIF}_{ki} + \beta_8\,\text{PDIF}_{ki} + \varepsilon_{ik} \qquad (1) \end{aligned}$$

where DIVERSIFICATION is represented by the variable DIRECT_{ik} to test our second proposition, and by the variable D_{ijk} to test the first one. Table 3 shows the descriptive statistics of the independent variables in Eq. (1). Table 4 shows the correlations between those variables.

4. Model estimation and discussion of the results

We estimated Eq. (1) using a probit model. To test the first proposition, D_{ijk} was the dependent variable (Model 1). To test the second proposition, the dependent variable was DIRECT_{ik} (Model 2). In estimating Model 1, we could have considered all the 56,025 cases, that is, the 875 cases where the dependent variable D_{ijk} was equal to 1, and the other 55,150 cases where it was equal to 0. This first option, however, would have implied a test of the hypotheses on the basis of an extremely unbalanced sample, where one of the states of the dependent variable was underrepresented (in fact, for only 1.56% of the sample was D_{ijk} equal to 1). Using the whole sample would yield an inefficient estimation of the model.

There was a better option: To define a balanced sample with a similar number of cases for both 1 and 0 values of the dependent variable. This procedure is called state-based-sampling and provides much more efficient estimations than a pure random sample when one of the states of the sample is overrepresented (Manski and

[8] If both the firm i and firms in the industry k have an average R&D expenditure level above the total average, R_{ik} will take high and positive values. If both the firm i and the firms in the industry k have expenditure levels below the total average, R_{ik} will also take high and positive values. Correspondingly, when the R&D expenditure level of the firm i is different from the R&D expenditure level of the firms in the target industry k, R_{ik} will take high but negative values.

Table 2
Variable description

Variable	Description	Values	Source
$DIRECT_{ik}$	Direct diversification (through internal development) of the firm i into target industry k during the period 2000–2001	Dichotomous 0,1	Infotel SABI
D_{ijk}	Diversification of the firm i in industry j into target industry k ($j \# k$) during the period 2000–2001	Dichotomous 0,1	Infotel SABI
PAT_{ik}	Technological intangible asset stock of the firm i measured by the sum of patents applied in the industry k, 1995–1999	Discrete (N° of patents)	European Patent Office
$LOGREV_i$	Logarithm of average revenues of the firm i, period 1990–1999	Continuous	Infotel SABI
$LOGPROFIT_i$	Logarithm of the average benefit after taxes for the firm i, period 1990–1999	Continuous	Infotel SABI
$CR4_k$	Concentration ratio in industry k, measured by the % of sales of the four biggest firms, 1999	Continuous (%)	SABI
R_k	Average R&D expenditure in industry k, 1990–1999	Continuous (mill. ptas.)	INE
$RDIF_{ik}$	Differences between the R&D expenditures of the firm i and industry k, average for the period 1995–1999	Continuous	Infotel INE
$ODIF_{ki}$	Difference between the output growth rate of the firm i and the industry k, average of the period 1990–1999	Continuous (%)	Infotel SABI INE
$PDIF_{ki}$	Difference between the average profit of the firm i and the industry k, measured for the period 1990–1999	Continuous (mill. ptas.)	Infotel SABI INE

Table 3
Descriptive statistics of the independent and control variables (Eq. (1))

Variable (units)	Average	S.D.
PAT_{ik} (no. patents)	9.20	169.50
$LOGREV_i$	21.6706	1.2366
$LOGPROFIT_i$	65.5706	7.6031
$CR4_k$ (%)	0.450	0.309
R_k (bill. ptas.)	68.9735	919.3292
$RDIF_{ik}$	−3.6E+23	4.8E+24
$ODIF_{ki}$	−0.962	9.974
$PDIF_{ki}$	0.144	44.726

McFadden, 1981). Following this procedure, from the initial sample we constructed a subsample that included all the cases where D_{ijk} was equal to 1 and a random subset of approximately 2% of the 55,150 cases where D_{ijk} was equal to 0. The resulting subsample included 1990 cases that we considered in our probit estimation of Eq. (1). This procedure yields consistent and unbiased estimations for all the coefficients but the constant term (Silverman, 1999): this is not a very significant limitation for our research because the constant term was of no interest in testing our hypothesis.

To test our first proposition we had to check the endogeneity and the simultaneity of the independent variable PAT_{ik} and the dependent variable D_{ijk}. In order to contrast the robustness of Silverman's model (1999) we checked the endogeneity hypothesis using Model 1 as the main (structural) equation. Using a time lag for the variable PAT_{ik} would have been an alternative method to validate the endogenous relationship. We had to reject this last method because it did not take into account the fact that the diversification decision may be taken before obtaining the patents for the target industry. In other words, after deciding to enter industry k, a firm could decide to develop and patent some inventions applicable to the industry k in order to smooth the entry barriers to that industry. To allow for this behaviour, we performed an

Table 4
Correlation matrix of independent and control variables Eq. (1), $n = 1990$

	PAT_{ik}	$LOGREV_i$	$LOGPROFIT_i$	$CR4_k$	R_k	$RDIF_{ik}$	$ODIF_{ki}$
$LOGREV_i$	0.081**						
$LOGPROFIT_i$	0.001	0.471**					
$CR4_k$	0.000	−0.038	0.003				
R_k	−0.001	0.041	−0.011	0.145**			
$RDIF_{ik}$	0.004	−0.039	0.011	0.083**	−0.098**		
$ODIF_{ki}$	0.001	−0.173**	0.017	0.021	0.002	−0.002	
$PDIF_{ki}$	0.000	0.163**	0.022	−0.024	−0.001	0.001	−0.624**

** Significant correlation at 0.01 level (bilateral).

endogeneity test applying some auxiliary regressions as suggested by Wooldridge (2002, p. 472–477). We can easily represent Eq. (1) as follows:

$$y_1^* = z_1\delta_1 + \alpha_1 y_2 + u_1 \tag{1'}$$

where y_2 represents the endogenous variable PAT_{ik}, z_1 the vector defined by the rest of variables and u_1 is the error term ε_{ik}. Given that:

$$y_2 = z_1\delta_{21} + z_2\delta_{22} + v_2 = z\delta_2 + v_2 \tag{2}$$

$$y_1 = 1[y_1^* > 0] \tag{3}$$

where (u_1, v_2) are independent from z, having a null mean and a bivariant normal distribution. Eqs. (1′) and (3) outline the structural equation; Eq. (2) is a reduced form for y_2, which will be an endogenous variable if u_1 and v_2 are correlated.

If we suspect that PAT_{ik} is endogenously determined by the dependent variable D_{ijk}, then estimators in Eq. (1) will be biased and inconsistent. To confirm this argument we needed an instrumental variable, which had to be correlated with the "suspect" variable but not with the error term in Eq. (1).

The instrument of PAT_{ik} we selected was the relationship between the average R&D expenditures and the average revenues for the period 1995–1999 ($\mathrm{RD/REV}_i$). Selecting this instrument we were assuming that R&D expenditures were not directly related to the likelihood of entering a specific industry. $\mathrm{RD/REV}_i$ would be a good instrument if it was not correlated to the error term in Eq. (1). We checked for that correlation finding that $\mathrm{RD/REV}_i$ and the residuals in Eq. (1) had a correlation coefficient of 0.016 ($p = 0.711$), while the correlation with PAT_{ik} was 0.166 ($p < 0.001$).

To perform the endogeneity test, the method proposed by Wooldridge (2002) is the following:

$$y_1^* = z_1\delta_1 + \alpha_1 y_2 + \theta_1 v_2 + e_1 \tag{4}$$

and supposing that

$$u_1 = \theta_1 v_2 + e_1 \tag{5}$$

with $\theta_1 = [\mathrm{Cov}(v_2, u_1)/\mathrm{Var}(v_2)]$ and e_1 being independent from z and v_2 (and consequently also from y_2). Under joint normality (u_1, v_2) e_1 is also normally distributed with mean $E(e_1) = 0$ and $\mathrm{Var}(e_1) = 1 - \rho_1^2$

$$(e_1/z, y_2, v_2) \sim \mathrm{Normal}(0, 1 - \rho_1^2)$$

where

$$\rho_1 = \mathrm{corr}(v_2, u_1).$$

Then, the new estimation would be:

$$P\left[\frac{(y_1 = 1)}{z}, y_2, v_2\right] = \Phi\left[\frac{(z_1\delta_1 + \alpha_1 y_2 + \theta_1 v_2)}{(1 - \rho_1^2)^{1/2}}\right] \tag{6}$$

As v_2 is known, Eq. (6) was estimated according to the following procedure: In a first regression,[9] we regressed the "suspected" endogenous variable, PAT_{ik}, on the rest of the exogenous variables and the instrument ($\mathrm{RD/REV}_i$), saving the residuals in the variable RESID_PAT (later v_2). In the second regression, we performed a new estimation of Eq. (1) including this time the new variable RESID_PAT.

Using this method, the common Probit statistic in the estimation $v_2(\theta_1)$ was converted into a null hypothesis exogeneity test for y_2, being H_0: $\theta_1 = 0$. Then, the coefficient of RESID_PAT (θ_1) should not be significantly different from zero. Results showed that this null hypothesis cannot be rejected (the coefficient RESID_PAT, θ_1 was 0.013695 its p-value being 0.5180). This result implies that the exogeneity hypothesis for variable PAT_{ik} cannot be rejected. In other words, our first proposition has to be rejected because PAT_{ik} is not endogenous. Moreover, as shown in the first column of Table 5, the rejection of the endogeneity proposition combined with the positive and significant coefficient of PAT_{ik} (Model 1) confirmed that innovation was driving the diversification direction but that diversification did not have any impact on the innovation direction.

We must remark, however, that this conclusion will be valid only under two assumptions: first, that the PAT_{ik} instruments are exogenous variables and second, that as y_2 (namely PAT_{ik}) is a count variable we had to suppose[10] that y_2 and u_1 were not correlated. In fact, under the exogeneity null hypothesis θ_1 was equal to zero and e_1 was equal to u_1, and consequently the v_2 distribution would be irrelevant. We must point out that the endogeneity test was valid even when the variable y_2 is a count variable (Wooldridge, 2002, p. 474). Finally, our second assumption also confirmed that the endogeneity of y_2 could be caused by the simultaneity with y_1, rather than by an omitted variable problem.

To test Proposition 2a we estimated Model 2a taking into account the 328 cases of direct diversification and a random subset of the cases with no diversification. To

[9] This regression, is available upon request to the authors.

[10] Contrastingly, if y_2 and u_1 were correlated, v_2 should be normally distributed. This was not true in our analysis, as long y_2 took positive and discrete values.

Table 5
Probit estimation of the diversification likelihood (Eq. (1))

	MODEL 1, Dep. Var. D_{ijk} (both direct and indirect div.) $n = 1990$		MODEL 2, Dep. Var. DIRECT$_{ik}$ $n = 875$		MODEL 2a, Dep. Var. D_{ijk} (only direct div.) $n = 1442$		MODEL 2b, Dep. Var. D_{ijk} (only indirect div.) $n = 1664$	
	Coef.[a]	Sig.	Coef.[a]	Sig.	Coef.[a]	Sig.	Coef.[a]	Sig.
Constant	−4.108*** (0.844)	0.000	10.947*** (1.471)	0.000	2.615* (1.472)	0.076	−8.470*** (0.986)	0.000
PAT_{ik}	0.197*** (0.027)	0.000	−0.0004 (0.001)	0.660	0.140*** (0.025)	0.000	0.132*** (0.025)	0.000
$LOGREV_i$	0.184*** (0.038)	0.000	−0.505*** (0.067)	0.000	−0.294*** (0.097)	0.003	0.307*** (0.071)	0.000
$LOGPROFIT_i$	0.0004** (0.0002)	0.034	0.0008 (0.009)	0.992	0.163** (0.067)	0.016	0.064 (0.054)	0.235
$CR4_k$	−0.985*** (0.160)	0.000	−0.806*** (0.257)	0.002	−1.685*** (0.268)	0.000	−0.832*** (0.199)	0.000
R_k	0.0001 (0.0005)	0.740	−0.0006 (0.007)	0.300	−0.0004 (0.0016)	0.814	−0.0008 (0.003)	0.820
$RDIF_{ik}$	0.0001 (0.0004)	0.674	−0.0001 (0.0011)	0.294	−0.0008 (0.0032)	0.788	−0.0002 (0.0007)	0.753
$ODIF_{ki}$	−0.005 (0.006)	0.441	−0.240** (0.011)	0.026	−0.019** (0.008)	0.020	0.008 (0.012)	0.475
$PDIF_{ki}$	0.0004 (0.001)	0.894	−0.002 (0.003)	0.359	−0.0003 (0.002)	0.989	0.002 (0.002)	0.508
−2log-lklhd	2441.267		1042.274		1178.687		1614.232	
R^2 McFadden	0.180		0.161		0.181		0.20	

[a] Standard errors in brackets.
* Significant at 10%.
** Significant at 5%.
*** Significant at 1%.

test proposition 2b we estimated Model 2b considering 547 cases of indirect diversification and a random subset of the cases where D_{ijk} was equal to 0.

Once we took into account these assumptions, the results of the estimations of Eq. (1) are shown in Table 5.

As shown in Table 5, the second column in Table 5 is concerned with our second proposition (Model 2), and shows that the variable PAT_{ik} is not significant in explaining the mode of diversification ($p = 0.660$). According to this result we had to reject our second proposition. Firm size (more explicitly $LOGREV_i$) was the only significant firm characteristic ($\beta_2 = -0.505$, $p < 0.001$) in our estimation, demonstrating that bigger firms are less likely to diversify through internal development. We also found that industry concentration ($CR4_k$) and OUTPUT DIFFERENCE ($ODIF_{ki}$) had a negative and significant impact on direct diversification ($\beta_4 = -0.806$, $p = 0.002$ and $\beta_7 = -0.240$, $p = 0.026$). This result seems to confirm the rejection of our second proposition, as the role played by technological resources in the choice of how to diversify is irrelevant when we control for industry variables.

Regarding Propositions 2a and 2b, the estimation of both their corresponding models yielded a positive and statistically significant coefficient ($p < 0.001$) of the independent variable PAT_{ik}. Subsequently, as shown in the third and fourth columns of Table 5, technological resources influenced diversification, whatever the mode of entry to the new industry.

Analysing control variables in Models 2, 2a and 2b, we observed that the firm size ($LOGREV_i$), had positive and significant coefficients in Model 2b, while it had a negative and significant coefficient in Model 2 and in Model 2a. These results confirmed a positive causal link between firm size and indirect diversification, and a negative relationship between firm size and direct diversification. The self-financing capabilities of the firm ($LOGPROFIT_i$), had a positive coefficient only when we estimated the relationship between innovation and direct diversification. This result may imply that in the future it could make sense to distinguish between diversification modes, because some internal variables could be affected by that distinction.

Industry concentration ($CR4_k$) had a significant ($p < 0.001$) and negative coefficient for the three models. Apart from the OUTPUT DIFFERENCE ($ODIF_{ki}$), none of the other industry control variables provided statistically significant results. More explicitly, our results showed a negative causal link (Model 2 and Model 2a) between the output difference between the firm and the target industry ($ODIF_{ki}$) and the choice of direct diversification.

5. Conclusions

This research has endeavoured to build on earlier research on the relationship between a firm's technological resources and the direction of its diversification, by trying to confirm the endogeneity of this relationship and by addressing the influence of innovation on the choice of the mode of diversification. Our results lead us to initially reject the endogeneity of the relationship between innovation direction and diversification, and to suggest that innovation drives diversification, but not the reverse. More specifically, our results seem to show that firms tend to enter industries where their technological resources can be applied, so that their technological resources will lead to competitive advantages.

One conclusion from the above is that, at least for Spanish firms and considering certain research restrictions that we comment on below, there is no bidirectional relationship between innovation direction and the diversification decision. In line with some financial papers on the diversification decision, such as Campa and Kedia (2002) and Maksimovic and Phillips (2002), our research confirms that value-maximizing firms would choose a diversification strategy based on pre-existing characteristics of the firm, such as knowledge assets. Our rejection of an endogenous relationship may reinforce the literature supporting the view that other factors such as organizational structure, fiscal strategies or management background may have a stronger impact on R&D decisions than the diversification strategy (Doi, 1985; Billings and Fried, 1999; Daellenbach et al., 1999).

The second important finding of this research is that we discovered some empirical evidence that, for Spanish firms, knowledge assets are not related to the diversification mode. This result is in line with some work that suggests that resources matter more in determining the extent of diversification rather than the mode of diversification, and that firms implementing direct diversification tend to pursue more related diversification than firms implementing indirect diversification (Chatterjee and Wernerfelt, 1991; Chatterjee and Singh, 1999). Perhaps more than innovation direction, it may be innovation relatedness that plays some role in the choice of the mode of diversification. Miller (2004) remarked that for high-R&D firms greater applicability of technology to a new industry was positively associated with the internal growth mode rather than acquisition. Claude-Guaudillat and Quelin (2004) established that firms will opt for external development to gain non-related competences, but will opt for internal development to gain related competences. The relatedness of innovation resources could also influence the endogeneity of the relationship between innovation and diversification. Miller's (2004) research supports the notion that diversifying firms have broader technology than non-diversifying firms. Unfortunately, we did not have adequate data to study the relationship between innovation-relatedness and the diversification decision. Finally, some interesting results arose from the analysis of control variables. It seems that, in line with previous research, firm characteristics might be more important than industry characteristics in the diversification decision.

We must note some limitations to our research as reported here. First, even though we were able to improve upon existing measurements of the diversification decision by including indirect diversification through controlled subsidiaries, we still left out of our study diversification through non-controlled subsidiaries. A second limitation is due to the lack of more detailed data and to the fact that we considered industries only at the two-digit level of the CNAE 93 classification. Because of this, a narrow definition of diversification was employed in this research, excluding diversification into very similar industries.

In addition to these limitations, technical knowledge encoded in patents does not fully represent the kind of tacit knowledge on which firms can build competitive advantage. Moreover, patents are an imperfect proxy for innovation because not all firms patent their new products and not all patents are brought to the market. With more complete data, this research could be replicated using structural equation modelling to specify more fully the relationship between innovation and diversification. In summary, this paper provides an enhanced econometric approach to solving the controversy over the relationship between innovation and diversification, replicates prior models (Silverman, 1999) using European data, and sheds some light on the relationship between innovation and diversification. However, it is just one step towards understanding the complex role of innovation in diversification strategies.

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