TECHNOLOGICAL DIVERSIFICATION AND INNOVATION IN EU FIRMS

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Abstract

This paper estimates the effect of technological diversity on R&D expenditures and innovation for a sample of European firms over a six-year period. Diversity is measured by a Herfindahl index of the Jaffe [1986] firm patent portfolio based index. Both R&D expenditures and innovation, measured as the firm's number of patents, are increasing with the degree of diversification of the firm. In particular it is shown that an increase of 10% in the technological diversification of the firm will conduct an increase of 2% in a firm's R&D expenditures and an increase of 12% on the number of patents. This result implies that the composition of the technological activity affects innovation providing some empirical evidence to the diversity-specialization debate

JEL classification: D21, O31, O32

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1 Introduction

The effects of R&D activity and innovation on productivity and growth have been widely recognized. Most of the new growth theory relies on the Schumpeterian idea that economic growth arises from industrial innovation. R&D investments are highly concentrated by industry, The composition of R&D investments and innovation can induce higher innovation. In particular, R&D and innovation may result to be linked to the firm's technological base. The aim of this paper is to identify and estimate the effect of technological diversity in generating innovation. It updates work by earlier researchers on the relationship between diversification and innovation (Scherer, 1984, Audretsch et al. 1999) using a technological measure of diversification (Jaffe, 1986, Branstetter, 1996) rather than a product approach. The questions addresses here are: Do technologically diversified firms invest more in R&D than less diversified ones? And, are they more innovative?

The importance of technological diversification has been purposed long time ago. Nelson (1959) considers that firms that diversify in their technological base are likely to benefit from new technological possibilities. Since many innovations occur to solve unrelated problems, companies that are more diversified might profit more from their own research activities, and therefore will capture more of the social benefits of their innovations. Technologically diversified firms may also tend to invest more in R&D. By using a measure of technological diversity at the firm level, this paper tries to explain part of the differences observed in R&D investments and innovation across firms. A firm can diversify its production for different motives such as gaining market power, making products compatible, avoiding risks, obtaining economies of scale in advertising and distribution of its products ... (Jovanovic, 1993). The theoretical literature, on the other hand, has recognized at least three reasons why technological diversification enhances innovation; first, it reduces the risk inherent to R&D projects (therefore firms might promote more basic research Nelson, 1959), second, as a way for firms to exploit complementarities among different activities (Jacobs, 1969, Glaeser et al., 1992, Feldman and Audretsch, 1999) and third, for firms to obtain higher private profits of their research programs (Nelson, 1959). Most part of the empirical work that relates diversification and innovation at the firm level is based on product diversification measures. Those studies have shown a trend between product diversification and different measures of innovation such as R&D intensity (Grabowski, 1968 and Teece, 1980), technical workers (Gort, 1962) or patents (Scherer, 1983). However, product diversification is not a clear measure of the firm's technological diversification and thus, it presents some problems. Two products that are classified in a different industry category can share the same science or technological base, in that case the positive relation between innovation and product diversification would indicate that there is a spillover effect among similar activities, i.e., knowledge useful for producing one product can help to produce others. In this case, the spillover effect would be due to the technological similarity among activities. Alternatively, two different products can indeed have a different science or technological base; in that case diversity-innovation relationship would be due to a different phenomenon, namely technological diversity. Using product diversification, it is not possible to distinguish between these two cases, moreover, products that are included in the same industry category can have a different science or technology base. All this makes difficult to interpret what the product diversity variable is actually measuring. Jaffe (1986) pioneered measuring the "technological position" of a firm and giving evidence about how knowledge spreads among firms that are "technological neighbors" among each other, Branstetter (1996) and Botazzi and Peri, (2002) also analyzes spillovers and their effects in promoting new innovation. However, none of these studies attempted to investigate whether there are knowledge spillovers within firms and, if there are, because firms are more diversified or more specialized in their technological activities? This investigation cannot give a clear-cut answer to distinguish among these possibilities, or even to claim that only one of them must be true, however it explores empirically these aspects.

This paper contributes to the literature with a microeconometric analysis of the effects of technological diversification on R&D and innovation. This is done by looking at R&D, innovation and the technological position of a panel of EU firms for the 1995-2000 period. Firm's innovation is measured by the number of patents it applies for. For each firm a patent portfolio based index (Jaffe, 1986) is calculated. Diversification is measured by a Herfindahl index of diversification of this portfolio. After controlling by size, and other characteristics of the firm, the results imply that technologically diversified firms invest more in R&D. An increase of 10% in the firm's technological diversification rate increases the R&D expenditures in 2% and the number of patents in 12%. The results are consistent with those from the product-diversification literature (Audretsch, 1999, Scherer, 1983). An important implication of this analysis is that if firm size and technological diversification are not related, there are other factors in addition to scale (and specialization) such as diversity spillovers that push private industry to spend more on R&D activities and to innovate. The rest of the paper is organized as follows. Section 2 presents the econometric specification. Section 3 describes the data that will be used. Section 4 offers the main estimation results relating diversity, R&D and innovation, and finally Section 5 concludes this paper.

2 Econometric specification

2.1 Diversification and R&D expenditures

R&D intensity (usually defined as R&D over sales) has been used in endogenous growth literature (Grossman and Helpman, 1991, Aghion and Howitt, 2000) as an indicator of long run growth of countries and firms. For this reason, it is important to examine the determinants of R&D when analyzing growth in countries. Diversification might promote an increasing R&D intensity, and therefore an increasing growth, at the firm level under certain conditions. These conditions are mostly the existence of spillovers among different technological activities (Jacob's effect) and the desire to risk-share their uncertainty. To test the impact of the degree of technological diversification on R&D expenditures at the firm level, the following equation can be estimated:

$$\begin{aligned} log(R\&D) = \alpha + \beta_1 \ log(sales_{it}) + \beta_2 \ (log(sales_{it}))^2 \\ +\beta_3 \ financial \ constraints_{it} + \beta_4 \ diversity_{it} + \gamma_i + \epsilon \end{aligned} \tag{1}$$

where $R\&D$ is firm i's R&D expenditures in year t, α is the constant term, $sales_{it}$ is firm i's sales in year t, $financial\ constraints_{it}$ is a measure of the external financial dependence of the firm, $diversity_{it}$ is the technological diversity of the firm and γ_i are a set of industry and country dummies[1]. The variable $financial\ constraints$ tries to capture the influence of imperfections in capital markets to restrain R&D expenditures and growth (Rajan and Zingales, 1998). The intuitive idea is that external reasons to the firm, in particular constraints to external financial funds can reduce the amount of R&D expenditures that the firm does[2]. To measure this effect three proxies have been used: total debt over total debt plus equity, and total current liabilities over total current assets and cash flows. Higher values of this variable reflect that the firm does not face financial constraints. A positive coefficient would indicate that firms without financial constraints invest more in R&D activities. The variable total current liabilities over total current assets indicates the firm's capacity to pay its short-term debts. Therefore a negative estimated coefficient would indicate that firms with a higher proportion of current assets (with more capacity to pay their debts) invest more in R&D. Also, it has been analyzed the effect of the cash flow on R&D expenditures. From a theoretical point of view Leland and Pyle (1977), Bhattacharya and Ritter (1985) and Kihlstrom and Matthews (1984) suggest that R&D

[1] This equation is not meant to be a realistic model of firm-level R&D spending. It does not mean that firms optimize R&D on the basis of their sales. Firm sales are included as a control for size. This is a standard specification in the R&D literature.

[2] See Hall (1992)

can be constraint by cash flow due to a moral hazard problem in transferring information about risky project from the firm to the investors. Hall (1992) and Mulkay et al.(2000) empirically found a negative relationship between cash flow and R&D expenditure for a panel of American firms. In order to control by this issue two different measures of cash flow has been incorporated in the estimation: logarithm of cash flow and logarithm of operating cash flow.

The key variable for this analysis is *diversity*. It has been constructed in basis of the Jaffe (1986) measure of technological proximity. For each firm its technological portfolio is calculated in the following way; with 46 technological fields indexed $j = 1, \cdots, 46$, if the ith-firm has N_i patents in the analyzed period, each patent can be assigned to a technological field, N_{ij} represents the number of patents in each of the 46 categories that the ith-firm holds, such that $\sum_{j=1}^{46} N_{ij} = N_i$. A Herfindahl index of concentration can be obtained for each firm and year. Subtracting this value from 1, it is obtained the variable *diversity*. Diversity measures the degree of technological diversification of the firm as follows:

$$diversity = 1 - \sum_{j=1}^{46} \left(\frac{N_{ij}}{N_i} \right)^2$$

A positive coefficient of the diversity variable in equation (1) would imply that more diversified firms invest more in R&D, supporting the Scherer's idea that technological diversity is more conductive to R&D activities, whereas a negative coefficient would indicate that firms with a technological base concentrated in similar activities invest more in R&D.

2.2 Diversification and innovation

Another possible proxy for lon-run growth is innovation generated at the firm level. Hall et al., Branstetter, Jaffe, Griliches ... use the numbers of patents that a firm applies for as proxy of innovation (a patent requires certain degree of product or method innovation). However, patents presents some problems as indicators of innovation, due, on the one hand, to the difficulty to measure the degree of technological advance that a patent represents, and on the other hand because not all the innovations are patented (specially those that are related to basic science). The relationship between technological diversity and innovation can be tested through the following equation:

$$patents_{it} = \beta_1 \; R\&D + \beta_2 \; K_{it} + \beta_3 \; diversity_{it} + \delta_i + \epsilon_i \qquad (2)$$

where the variable $patents_{it}$ is the number of patents of the ith firm in period t. It represents the innovations of the firm. $R\&D_{it}$ is the log of the R&D expenditure of the ith firm in period t, K_{it} represents the spillover term (in logs) among the firms in the sample and it is constructed as in Jaffe (1989) including for each firm an available "pool" of outside R&D [3], δ_i is a set of country and sector dummies and ϵ is the error term. The variable *diversity* is measured as in equation (1). A positive coefficient of the *diversity* variable would indicate that the greater the degree of diversification among firms, the easier it will be for firms to implement new ideas. This approach was pioneered by Scherer (1983) who estimates the relationship between innovation and diversity at the firm level. Unfortunately, equation (2) presents a problem. When the number of patents increases and its distribution does not change, the diversification index remains constant (the variable *diversification* would be independent of the *number of patents*). However, the diversity variable can be reflecting the fact that a firm has few patents because firms with less than 46 patents (the total number of groups) do not have the same chances to diversify as firms with more than 46 patents (clearly a firm with one patent will have diversification zero, and a firm with two patents the higher value that the diversification index can take is is 0.5). That poses a serious problem in the estimation of equation (2). To attempt to control by this fact, two different approaches have been taken:

First of all, three different groups of firms are considered: firms with less than 10 patents and with less than 10 patents are estimated separately[4], firms with less than 20 patents and more than 20 patents and finally three groups with firms with less than 10 patents, between 10 and 20 patents and more than 20 patents. Taking firms that have the same possibilities to diversify, the dependence of the diversity variable with the number of patents is reduced. The comparison of the results allows to obtain some idea of the stability and robustness of the results.

Second, a non-bias diversity estimator has been used. Hall (2000) proposed the following variation of the Herfindahl index. In that way, diversity is measured as follows:

$$adjusted\ diversity = \left(1 - \sum_{j=1}^{46} \left(\frac{N_{ij}}{N_i}\right)^2\right) \left(\frac{N_i}{N_i - 1}\right)$$

[3]See Section 2 for a detail analysis of the construction of this variable

[4]Ten seems a reasonable number of patents because the firm that most diversified does it in 10 different groups.

3 On data

This investigation uses data on 544 firms for 15 EU countries for the period 1995-2000. For each firm there are yearly data on R&D expenditures, sales, liabilities and equity and the main SIC industry classification for the whole period at the 4th digit of desegregation. All financial data are real annual figures deflated to the base year 1995 using country's GDP deflactors. Financial data come from the Worldscope Global database and GDP deflactors from the OECD database.

The firm selection is due to the availability of R&D expenditures for those firms in the database. Only EU firms that report R&D in at least three years have been selected. It causes a possible selection bias, however in this context taking firms that do not report R&D expenditures can produce additional problems. If a firm patents without reporting R&D activities can be possibly for two reasons: first, that the firm does not do R&D activities, in that case is difficult to justify where this patenting activity comes from, but by developing already invented process or products or by imitating from other firms (Scherer, 1983), since patents are used as a proxy for inventive activity, those companies would be accounted as if they were innovating when they are not doing so. The second case is if the firm does R&D but do not report it, for instance in the case of small firms where the R&D activity is counted in other financial statements. When those firms are taking in the sample, their expenditures on R&D are counted as zero, when the firms are indeed making some expenditure. The interest of this paper lies on the innovation point of view, for this reason it seems reasonable select only those firms that are innovating and whose expenditures in innovation can be account in this case through R&D. Table 1 shows some summary statistics for the firms in the sample broken down into 15 industry categories.

Table 1: Comparison of average R&D spending and sales by industry reported to Worldscope
period 1995-2000 in millions of U.S. dollars

	No of firms in the sample		average				
Industry	all firms	% over total	sales	max. sales	R&D	max R&D	$\frac{R\&D}{sales}$
1 Chemicals and oil, gas, coal	63	12%	14866	751445	993	107953	7%
2 Electronics	104	19%	2354	73894	188	5445	8%
3 Drugs, cosmetics and health care	43	8%	2051	17690	223	2753	11%
4 Construction	31	6%	1443	15517	24	560	2%
5 Recreation	13	2%	1785	8657	29	299	2%
6 Metal products manufactures	32	6%	2474	15989	27	207	1%
7 Machinery and equipment	62	11%	1267	10245	59	1412	5%
8 Food, beverages and tabacco	36	7%	5598	57404	76	1119	1%
9 Automotive	22	4%	21345	154429	913	5973	4%
10 Telecommunications, electric services	28	5%	8036	46024	116	1037	1%
11 Electrical	20	4%	2447	17312	65	894	3%
12 Textiles	10	2%	595	4204	4	17	1%
13 Transportation, aerospace	10	2%	3969	14855	178	1473	4%
14 Others: paper, printing	59	11%	2803	27154	32	482	1%
15 Professional and scientific instrument	11	2%	393	3566	23	235	6%
Total	544						

By industry, the most R&D-intensity (measured through this paper as R&D over sales) is in the drugs, cosmetics and health care industry (11%), followed by electronics (8%), and chemicals industry (7%). The firm selection has been done based on the R&D availability, therefore firms for any sector has been taken. It would be expected that the sample would be bias through sectors that report more R&D, however, there are also firms in less intensive R&D sectors such as Textiles (2% of the sample), Food and beverages (7% of the sample) or Construction (6% of the sample). This Table also indicates that the largest firms, measured as sales, in the sample are in the Automotive sector and in the Chemical sector, being the latter more R&D intensive. Table 2 shows that the most R&D-intensity countries in this sample are Sweden, Netherlands and Denmark (7%), closely followed by Germany and France. This table indicates that there are many U.K.'s firms in the sample (253 firms), following by Germany and France. Luxembourg and Spain are the countries with less firms in the sample. The countries with the largest firms are France, Germany and Netherlands, while Greece, Spain and Denmark not only have few firms in the sample but also are they the smallest (in the case of Denmark those firms are highly R&D intensive). The firm distribution per country and industrial sector is reported in Table 3.

Table 2: Comparison of average R&D spending and sales by country reported to Worldscope

	No. of firms	Sales	R&D	R&D/Sales
France	56	11840	1108	5%
Germany	70	10653	504	6%
Greece	13	167	2	2%
Italy	23	8133	175	4%
Spain	2	206	8	4%
Sweden	27	3966	214	7%
UK	253	2400	48	4%
Lux	1	943	0	0%
Netherlands	23	10814	257	7%
Finland	39	2008	57	3%
Austria	10	1551	21	2%
Belgium	6	3267	133	3%
Denmark	10	870	62	7%
Ireland	11	1261	18	3%
Average		4148	186	

Table 3: Distribution of firms per country and industrial sector (no. of firms in the sample)																
	Industries															
Countries	1	2	3	4	5	6	7	8	9	10	11	12	13	14	15	All
France	7	10	5	2	3	6	3	3	4	1	3	0	1	7	1	56
Germany	11	10	7	4	0	3	15	0	8	2	3	1	1	2	3	70
Greece	1	4	1	2	1	1	0	2	0	0	0	0	0	1	0	13
Italy	3	2	1	1	0	1	5	2	3	3	1	0	0	0	1	23
Spain	0	1	0	0	0	0	1	0	0	0	0	0	0	0	0	2
Sweden	1	6	2	1	0	2	4	1	3	2	2	0	0	3	0	27
UK	24	60	23	15	7	10	21	12	4	17	10	7	8	30	5	253
Lux	0	0	0	0	0	0	0	1	0	0	0	0	0	0	0	1
Netherlands	5	3	0	1	0	1	6	3	0	0	0	0	0	3	1	23
Finland	4	5	1	2	1	5	4	5	0	3	0	1	0	8	0	39
Austria	2	0	0	1	0	1	2	2	0	0	0	1	0	1	0	10
Belgium	3	0	0	0	1	1	0	0	0	0	0	0	0	1	0	6
Denmark	2	3	2	1	0	0	1	1	0	0	0	0	0	0	0	10
Ireland	0	0	1	1	0	1	0	4	0	0	1	0	0	3	0	11
Total																544
See Table 1 for sectors definitions																

In this sample, French firms are in the sector of Chemicals (12.5%), Electronics(17.9%), and Other manufacturing activities (12.5%), German firms mostly produces in Machinery and equipment (20%) and Chemicals (15.7%), Greece, Sweden, UK and Denmark have most of their firms in Electronics sector. Italian companies have their activities focus in Machinery and Equipment (21.7%), firms from Netherlands are mostly in Chemicals (21.7%) and Machinery and equipment (26.1%). Finish companies have their activities in Other manufacturing activities (20.5%). Firms from Austria are located in the sector of Chemicals (50%). And finally Irish companies are in Food (36.4%) and Other manufacturing sector (27.3%) Patent data are taken from the Depatis database (this is the German Patent Information System on the Internet provided by the German Patent and Trade Mark Office). For each firm and year all the EP[5] patents (European patents) have been selected. The reason to chose EP patents have been based in terms of comparability of patents among EU countries. Since the sample has few firms, I want to get as much patent information as possible from these firms. Most part of empirical works have taken patents the firm applies for in the US. Trademark Office, because the easy availability of those patents. However, a small proportion of European firms patent in the U.S.: for 100 patents of German firms in Germany, there are 30 patents in the U.S., this relationship also holds for France. For 100 patents of British firms in U.K., there are only 20 patents in the U.S.[6]. Taking U.S. patents can be an advantage because the quality of the patent

[5]The same study have been done with WO (World Patents) and firm's national patents without significative changes.

[6]Source: Eaton and Kortum (1999). They take patents application data form WIPO. The data are an average of 1988-1990

can be higher due to the fact that costs to patent are higher in the U.S. than in the own country. In that sense, patents can be a better measure of innovations. Unfortunately, in my sample, I would not obtained patent information of medium size firms, that patent less in the U.S. A possible solution would consist in taking those patents that the firm applies for in its country (own patents). This selection presents a problem because cost of patent (own patents) differ among EU countries. I decided to take EP patents for two reasons, first, there are many of the firms in my sample with those patents, and second, because the cost of and EP patent is very similar among firms. There are some differences depending on the number of countries the firm designates, but those differences on average are not as large as the different cost of own patents.

Each patent is classified following the IPC (International Patent Classification) system from the WIPO (World Intellectual Property Organization). This system includes 627 patent classes at the three-digit level (in its 7th edition) though the classification system actually contains thousands of subclasses. The 627 patent classes have been grouped in 48 categories in the following way. The basic classes are taken from Hall et al. (2001). They grouped the 417 US patent classes into 36 technological categories. I matched the 627 IPC classes in to the 417 US classes (this information is available at the US Patent and Trademark webpage), initially getting 36 classes. To make this grouping more accurate and better adjusted to the IPC classification some groups have been changed until finally obtaining 48 categories (that seems a reasonable number of classes, Jaffe (1986) constructs 49 categories, Branstetter and Sakakibara (1998) and Sakakibara (2001) make 50). This last step was essentially ad hoc based on the class's names and there is a certain degree of arbitrarily in this process (although the grouping process is based in a technology and not in a product approach). Firms with less than two patents have been removed from the sample. Table 4 shows the average R&D expenditure and sales per industrial sector for those firms that have at least one patent from 1995 to 2000 (381 firms).

There are some variations with respect to Table 1, illustrating the fact that firms that patent are slightly more R&D intensive.

Table 4: Comparison of Average R&D Spending and Sales by industry reported to Worldscope for firms that patent period: 1995-2000 in millions of U.S. dollars				
Industry	No. of firms	Sales	R&D	R&D/Sales
1 Chemicals and oil, gas, coal	47	17170	1307	8%
2 Electronics	65	1984	174	9%
3 Drugs, cosmetics and health care	35	2508	273	11%
4 Construction	22	1617	31	2%
5 Recreation	7	1753	40	2%
6 Metal products manufactures	19	3102	37	1%
7 Machinery and equipment	51	1260	69	6%
8 Food, beverages and tabacco	21	8318	126	2%
9 Automotive	19	23722	1012	4%
10 Telecommunications, electric services	16	11152	167	2%
11 Electrical	17	2764	75	3%
12 Textiles	5	724	4	1%
13 Transportation, aerospace	7	4903	242	5%
14 Others: paper, printing	42	3284	41	1%
15 Professional and scientific instrument	8	419	23	6%
Total				381

Table 5 indicates that sectors with more patents are automotive, chemicals and transportation (including aerospace) while textiles is the sector where there are less patents per firm. This fact is also shown in Table 6, through the number of firms that do not have any patent by industry. Textiles and Food, beverages and tabacco are the sectors with larger number of firms that do not have patents in the sample. The main differences between the average number of patents for firms with non zero patents with respect of taking EP or Own patents are in recreation sector (there are more EP than Own patents), and in automotive, telecommunications, electrical, and transportation sectors (where there are more Own patents than EP patents).

Table 5: Patents-industry relations								
	Average no. of patents for all firms		Average no. of patents firms with non zero patents		Total no. of patents		Standard deviation	
Industry	Own	EP	Own	EP	Own	EP	Own	EP
1	232	205	311	275	14617	12926	919	734
2	54	78	87	125	5626	8126	376	506
3	93	116	115	142	4010	4967	479	350
4	25	28	36	40	781	872	86	100
5	3	67	5	125	34	874	3	323
6	17	18	29	30	559	575	49	45
7	29	18	35	22	1809	1110	63	32
8	11	81	19	139	403	2921	51	385
9	1314	511	1522	592	28909	11240	2676	1271
10	79	45	139	78	2219	1246	352	199
11	89	60	104	71	1774	1199	188	172
12	1	2	3	4	14	22	1	6
13	166	111	238	158	1663	1108	617	289
14	13	16	18	22	765	915	69	82
15	9	40	12	55	98	440	22	139
See Table 1 for definitions of sectors								

Table 6: No. of firms that do not report any patent per industry				
Industry	Own	EP	% over total Own	% over total EP
1	23	16	37%	25%
2	49	53	47%	51%
3	15	9	35%	21%
4	10	15	32%	48%
5	6	8	46%	62%
6	16	16	50%	50%
7	18	21	29%	34%
8	21	17	58%	47%
9	4	6	18%	27%
10	13	13	46%	46%
11	5	8	25%	40%
12	6	6	60%	60%
13	5	4	50%	40%
14	24	21	41%	36%
15	3	4	27%	36%
See Table 1 for definitions of sectors				

The countries that patent more per firm are Germany and France, followed by Belgium, this is presented in Table 7. This Table also implies that there are some differences depending on whether EP or national patents are used. This fact is particular relevant for Finish firms (it only has 34 Own patent, while it has 2033 EP patents. This difference is because the company "Nokia" is included in this sample, and it has a higher proportion of EP patents than national patents.)

Table 7: Average number of patents per firm

	No. of EP patents	average no. EP patents per firm	No. of Own patents	average no. Own patents per firm
France	12468	223	19972	357
Germany	20352	291	37418	535
Greece	5	0	0	0
Italy	1152	50	519	23
Spain	20	10	26	13
Sweden	1477	55	1070	40
UK	5541	22	2293	9
Lux	0	0	0	0
Netherlands	2248	98	508	22
Finland	2033	52	34	1
Austria	101	10	96	10
Belgium	1094	182	251	42
Denmark	628	63	46	5
Ireland	54	5	0	0

Table 8 shows the size distribution of firms in the sample. A large number of medium-sized firms are included, (most part of firms have a size between 100 million of U.S. dollars and 1 billion of U.S. dollars) although these firms account for less than 4% of total sales of firms in the sample, and 2.2% of expenditures in R&D. Most part of sales and R&D expenditures are made by firms with more than 10 billions of U.S. dollars of sales (83.7% of total R&D in the sample). This table also shows that there are not significative differences in Own or EP patents depending on the size of the company, that is, bigger firms do not patent proportionally more in EP than in Own patents.

Table 8: Size distribution

size class (averaged sales)	No. of firms	No. of firms/total	Own patents no. of firms that patent	Own patents % firms that patent	EP patents no. of firms that patent	EP patent % firms that patent	% of total sales	% of total R&D
Less than 1 million	0	0.00	0	0%	0	0%	0%	0%
1 to 10 million	10	0.02	3	0.9%	8	2%	0.0%	0.1%
10 million to 100 million	108	0.20	45	13.8%	34	10%	0.2%	0.3%
100 million to 1 billion	207	0.38	119	36.6%	126	39%	3.0%	2.2%
1 to 10 billion	163	0.30	113	34.8%	112	34%	22.2%	13.7%
Over 10 billion	56	0.10	45	13.8%	47	14%	74.5%	83.7%
Total	544		325		327			

Larger firms tend to patent more. The highest proportion of firms that patent are in the size class of 100 millions to billion of U.S. dollars (39%), followed by firms in the range of 1 to 10 billions (34%). Only 14% of big firms (over 10 billion of U.S. dollars in sales) patent in the sample. This fact can be done because some of those large companies are in sectors with low patenting activity. Therefore, not only size is important to do patent activity but it is also very important the sector where the firm makes its activities.

4 Estimation results

4.1 Diversification and R&D expenditures

The estimation results of equation (1) are shown in Table 9. Column (i) shows that diversity has a significant effect on R&D. Including size squared as in column (ii) gives almost identical results. This last variable tries to capture possible non linearities in the relationship between R&D and firm's size. The different debt measures give very different results. Firms with a higher proportion of current liabilities over current assets invest in R&D, columns (i) and (ii), this as expected shows the positive relationship between the proportion of current assets and R&D. Total liabilities over total liabilities plus equity, columns (iii) and (iv), has a positive although not very significant relationship with R&D indicating the fact that firms without financial constraints invest more in R&D[7]. The next columns, (v) to (vi) analyze the effect of cash flow on R&D. Cash flow has a positive relationship with R&D expenditures. Columns (ix) to (xiii) show a more general measured of the diversity is used. Here diversity1 is a constant over the six-year period per firm. Diversity1 has been calculated using all firm's patents over the six-year period. Again there is a positive and significant relationship between diversity and R&D expenditures The results suggest that more technological diversified and with less leverage firms invest more in R&D.

[7] Similar estimations have been calculated using two additional measures of financial constraints in the firm: current liabilities over total liabilities plus equity, and total liabilities minus current liabilities over total liabilities plus equity. These variables have positive sign but they are not very significative.

Table 9: OLS estimation of R&D determinants. t-statistic between brackets
All regressions include country and industry dummies. All financial variables are deflacted with the GDP deflactor
Dependendent variable: log(rd)

	(i)	(ii)	(iii)	(iv)	(v)	(vi)	(vii)	(viii)	(ix)	(x)	(xi)	(xii)	(xiii)
log sales	0.88	-0.79	0.85	-0.96	0.91	0.80	0.93	0.84	0.84	0.81	0.89	0.72	0.76
	(42.25)	(-5.26)	(39.15)	(-6.00)	(20.74)	(22.42)	(41.64)	(23.76)	(54.26)	(50.71)	(27.87)	(27.66)	(29.34)
$(logsales)^2$		0.14		0.15									
		(11.27)		(11.41)									
debt1	-0.32	-0.26					-0.29	-0.31	-0.29				-0.29
	(-7.00)	(-6.02)					(-6.11)	(-6.61)	(-8.16)				(-8.10)
debt2			0.01	0.21						-0.05			
			(0.10)	(2.47)						(-0.80)			
cash1					0.05						0.04		
					(1.15)						(1.36)		
cash2						0.09		0.10				0.14	0.14
						(2.78)		(3.05)				(5.89)	(6.01)
diversity	0.24	0.22	0.25	0.24	0.25	0.23	0.23	0.21					
	(4.72)	(4.56)	(4.68)	(4.89)	(4.77)	(4.13)	(4.35)	(3.94)					
diversity1									0.27	0.28	0.21	0.23	0.22
									(5.65)	(5.80)	(4.45)	(4.62)	(4.52)
constant	-0.82	4.19	-0.80	4.66	-1.09	-0.76	-0.87	-0.86	-1.00	-0.98	-1.45	-0.93	-1.02
R^2	0.82	0.84	0.82	0.84	0.85	0.84	0.83	0.85	0.81	0.80	0.85	0.82	0.83
Adjusted R^2	0.82	0.84	0.81	0.84	0.85	0.83	0.83	0.84	0.80	0.80	0.84	0.82	0.83
Sample	965	965	950	950	811	810	891	810	1638	1640	1359	1372	1372

debt1=total current liabilities/ total current assets
debt2=total liabilities/(total liabilities+equity)
diversity is a year-variable for any firm
diversity1 is a constant, it has been calculated using all firm's patents over a six-year period. It is different among firms.
cash1 is logarithm of operating cash flow
cash2 is logarithm of total cash flow

A basic econometric issue such as simultaneity and unobservables can arise; R&D expenditures, debt and technological diversity can be simultaneously determined for the firms. In that case, it would not be exogeneity of debt or technological diversity in estimating R&D expenditures. To control for this possible problem Table 10 explores the use of instrumental variables in the basic regression. In particular, all the independent variables are lagged one period. As can be seen, the results are essentially the same as in previous estimations. This result illustrates again the positive relationship between technological diversity and R&D expenditures on the one hand, and on the other hand, the negative effect of debt or cash flow constraints on R&D.

Table 10: OLS estimation of R&D determinants.
All independent variables are lagged one period.
t-statistic between brackets
All regressions include country and industry dummies.

	(i)	(ii)	(iii)	(iv)	(v)
log sales	0.87	0.82	0.91	0.77	0.81
	(37.59)	(35.32)	(17.95)	(19.27)	(20.62)
debt1	-0.34				-0.33
	(-6.57)				(-6.24)
debt2		0.04			
		(0.45)			
cash1			0.02		
			(0.47)		
cash2				0.10	0.11
				(2.85)	(3.02)
diversity	0.26	0.30	0.27	0.26	0.23
	(4.52)	(5.28)	(4.71)	(4.34)	(3.91)
constant	-0.67	-0.52	-0.90	-0.48	-0.58
R^2	0.83	0.83	0.85	0.84	0.85
Adjusted R^2	0.82	0.82	0.85	0.83	0.84
Sample	789	781	661	660	660

debt1=total current liabilities total current assets
debt2=total liabilities/(total liabilities+equity)
diversity is a year-variable for any firm
diversity1 is a constant
cash1 is log of operating cash flow
cash2 is log of total cash flow

To summarize, this analysis is consistent with other studies that relate debt and sales with R&D expenditures. Firms that have more debt are less invest less in R&D. Size, measured as sales, is an important determinant of R&D, however it does not seem to affect R&D intensity (when introducing sales and sales squared in the regressions the results are not significative different from zero). To analyze this idea the it is estimated the determinants of R&D intensity (measured as R&D expenditures over sales). The results are reported in Table 11.

Table 11: OLS estimation of determinants of R&D intensity
t-statistics between brackets
Dependent variable: R&D/sales

	(i)	(ii)	(iii)
sales	-0.12	-0.20	-0.16
	(-5.56)	(-5.60)	(-4.67)
debt1	-0.32		-0.31
	(-7.00)		(-6.61)
cash2		0.09	0.10
		(2.78)	(3.05)
diversification	0.24	0.23	0.21
	(4.72)	(4.13)	(3.94)
constant	-0.82	-0.76	-0.86
R^2	0.51	0.50	0.53
adjusted R^2	0.49	0.48	0.51
sample	965	810	810

Regressions include country and industry dummies

The results imply that size, technological diversification and financial constraints also affect R&D intensity, that is a proxy of the proportion of the wealth that firms invest in R&D. All the parameters estimated are with the expected sign and significatively different from zero. An important result is the positive relation between R&D and technological diversity. The positive coefficient suggest that a strong presence of different technological activities at the firm level induces firms to invest in R&D. The basic message is that more technological diversified firms, even after controlling by size and financing are ahead in R&D. In all estimations the R^2 is slightly over 0.8, indicating a reasonably good fit (except on the R&D intensity estimation). To determine the effect of size, technological diversification and financial constraints,

4.2 Diversification and innovation

Table 12 presents the result of the estimation of equation (2) by a Binomial Negative model. It has been chosen the Binomial Negative specification because the dependent variable counts the number of patents a firm applies for, that is a count variable. In addition to that there can be some overdispersion in data. That is that the variance of the variable can be larger than the mean, because some firms can have zero patents a year and several other years. For this reason a Poisson specification can be misspecified.

In order to take account of externalities among firms, it has been added a spillover (K) variable to the specification, trying to measure the fact that firms that have an larger available R&D pool can have more incentives to innovate, since the cost can be lower. An important difference between the spillover variable and the technological diversification, is that the spillover is external to the firm, while the diversification degree is a decision varible for the firm, that means that the firm can chose how wide or narrow is its research program.

The spillover variable is defined as in Jaffe (1986): $K_i = \sum_{j \neq i} P_{ij} R\&D_j$

The spillover that the ith-firm receives (K_{it}) is the weighted average of all other firms' R&D spending ($R\&D_j$). The weights (P_{ji}) are constructed using the proximity of the firms in their technology space:

$$P_{ji} = \frac{F_i F_j'}{\Big((F_i F_i')(F_j F_j')\Big)^{1/2}}$$

where $F_i = (f_i, \cdots, f_k)$ is the firm's technological space of a firm. It is measured using the distribution of the firm's patents in the different technological areas (as in previous sections, 46 areas have been considered). A possitive value of the estimated coefficient means that firms benefit from the research activities taken by others firms in a similar science base as them.

To remove this bias from the unobserved heterogeneity in the estimation, a proxy of the past values of the dependent variable previous to the estimation sample is added to the estimation. The variable *pat* is a dummy variable that takes the value of 1 if the firm has at least one patent from 1985 to 1990, and 0 otherwise. Table 13 shows the Negative Binomial estimation of equation (2). This estimation method is chosen because on the one hand, the dependent variable are counts of the number of patents a firm applies for, and on the other hand, there can be some overdispersion of those data (a firm can have zero or some patents in the analyzed period). Clearly a higher technological diversity implies more innovation, this is shown in column (i). In particular an increase of 10% of the technological diversity of the firm will increase the patent activity of that firm in about 16%. The spillover variable is also significative different from zero and positive, showing the fact that firms benefit from the available pool of knowledge from other firms that share a common base science. The variable *pat* is also significative indicating that if firms have patented in the past, it has a positive effect on present patenting activity, that is, there is certain persistence in the innovative activity. Columns (ii) to (vi) of Table 13 shows the same estimation specification, when different groups are made. In particular, column (ii) shows the estimation for firms with more than ten patents, column (iii) for firms with less than ten patents, column (iv) for firms with more than twenty patents, column (v) for firms with less than twenty patents and finally column (vi) for firms between ten to twenty patents. Increases of 10% of the technological diversity increases approximately the number of patents the firm applies of 7.5%, columns (ii) to (vi) in Table 13. For firms with more than twenty patents this effect is considerably smaller, although it increases for firms with less than twenty patents. Finally firms that have between ten to twenty patents the diversity impact is neglectible. This result is probably because the small sample of this estimation (only 103 observations). In all the cases R&D expenditures influences positively innovation, although for firms with less than twenty patents this relationship is very weak (columns (iii), (v) and (vi)). Perhaps the variability in the R&D activity undertaken by firms is not related with the variability of the dependent variable since the dependent variable in that case and by construction can take very few different values. Firms that patent more seem to benefit more from the available R&D stock, although the estimated parameter of the spillover variable is bigger for firms with more than ten patents than for firms with more than twenty patents.

In order to control by possible bias of the diversity variable, the same estimations have been calculated using a variation of the Herfindahl index proposed by Hall (2000). The adjusted diversity has a significant although much smaller effect on innovation than in previous estimations, that is due to the fact that firms with less patents and therefore more likely to be more technologically concentrate are given a higher weight in the estimation. Columns (vii) to (xii) of Table 13 show the binomial negative estimation of the number of patents with the adjusted technological diversity variable. Column (vii) shows that R&D expenditures, spillovers and past patenting activity affects positively to innovate. The estimated parameter of the adjusted technological diversity is also significatively different from zero and positive although it has a smaller value than diversity. Columns (viii) to (xii) show similar results to columns (ii) to (vi). Those results can be seen as a lower bound of the technological diversity effect on innovation, 10% increase on diversity can increase at least the number of patents on 6.9%. And analyzing this effect by groups of firms, the estimated parameter of the adjusted diversity variable is stable around 0.4 (except for firms with ten to twenty patents), what implies that an increase on diversity of 10% at least increases the number of patents in 4%. The spillover effect (K) affects more to firms with a large number of patents (for firms with more than ten patents, columns (viii) and (x)). For those firms an increase in the available knowledge pool of 10% will increase their patent activity in at least 3% (column (i)).

From this estimation three results can be highlighted, first, the positive relationship between number of patents and R&D expenditures (this can be seen as a measure of firm's size), second the persistence of the patent activity (the dummy *pat* is significanctively different from zero in all cases), and third, the importance of both spillovers with firms that share a common base science and the effect of technological diversity in the firm. This last result suggests that on the one hand, firms benefit from knowledge generated in other companies that is similar to the one that they do, and at the same time they profit from research activities done in the firm, such that the wider the technology the firm undertakes, the more profitable is for the company.

Table 12: Binomial negative estimation of the number of patents.
z-statistics between brackets
All regressions include country and industry dummies
Dependent variable: number of patents

		np1	np2	npa1	npa2	npa3		np1	np2	npa1	npa2	npa3
	(i)	(ii)	(iii)	(iv)	(v)	(vi)	(vii)	(viii)	(xix)	(x)	(xi)	(xii)
log R&D	0.90	0.78	0.05	0.62	0.19	0.01	1.05	0.81	0.10	0.64	0.27	0.01
	(19.78)	(13.13)	(1.19)	(8.59)	(4.54)	(0.20)	(23.38)	(13.73)	(2.45)	(8.85)	(6.14)	(0.24)
K	0.32	0.61	0.04	0.46	0.06	0.00	0.55	0.66	0.06	0.50	0.10	0.00
	(3.01)	(3.60)	(0.52)	(2.22)	(0.78)	(0.04)	(4.68)	(3.86)	(0.82)	(2.40)	(1.22)	(-0.03)
diversity	1.69	0.75	0.87	0.86	1.09	-0.02						
	(12.01)	(2.92)	(9.09)	(2.48)	(11.39)	(-0.14)						
adjusted diversity							0.69	0.37	0.28	0.57	0.40	-0.01
							(5.27)	(1.46)	(4.34)	(1.62)	(4.93)	(-0.09)
pat	0.60	1.22	0.17	1.18	0.32	0.06	0.72	1.20	0.22	1.17	0.40	0.05
	(5.53)	(7.10)	(2.44)	(6.30)	(4.28)	(0.48)	(6.39)	(6.96)	(3.29)	(6.24)	(5.14)	(0.38)
constant	-5.06	-6.80	0.91	-5.12	0.22	2.53	-7.66	-6.89	0.54	-5.20	-0.27	2.56
Log likelihood	-3514	-2191	-897	-1704	-1418	-250	-3561	-2194	-930	-1706	-1467	-251
Sample	890	435	455	314	576	103	890	435	455	314	576	103

Column (i) and (vii) all firms
np1: firms with more than 10 patents
np2: firms with less or 10 patents
npa1: firms with more than 20 patents
npa2: firms between one to 20 patents
npa3: firms between 10 to 20 patents
pat: dummy variable, one if firm has patented in the past, zero otherwise

Table 13 shows OLS, fixed and random effects estimation of equation (2). The dependent variable is the logarithm of the number of patents, when the number of patents is zero it has been changed to one. Column (i) indicates, as in the negative binomial estimation, that R&D, spillovers, technological diversity and having patents in the past affect positively to innovate. Next columns (ii) and (iii) show the fixed and random effects estimations. The main differences are the value of the estimated parameter of the spillover (in the fixed effects estimation), and the slight decrease of the value of the parameter of the technological diversity variable. Table 13' shows the same estimation with the variable adjusted diversity. The estimated values are smaller than in the previous table. Columns (i) to (iii) show again the positive relationship between technological diversity and patenting activity. Columns (iv) to (viii) of Tables 14 and 14' show OLS estimation of equation (2) when the sample is divided in groups depending on the number of patents the firm applies for. The results indicate that there are no significative differences for groups of firms, in all cases in Table 13 the estimated parameter of the diversity variable is around 0.4 and significative except for firms that have between ten to twenty patents. This result can be because the small sample available for those kind of firms. The estimation results changed when the adjusted diversity variable is used, specially in fixed and random effects (columns (ii) and (iii) in Table 14'). While random effects presents a positive, significant although small estimated parameter, fixed effects estimation shows that technological diversity affects positively patent activity but the result is not very significative.

The OLS estimation is consistent with previous estimations. Again, firms that have conducted patenting activity in the past patent more. R&D expenditures, spillovers and technological diversity affect innovations at the firm level.

Table 13: OLS, Fixed (F.E.) and Random (R.E.) effects estimation t-statistics between brackets Dependent variable: log(number of patents)								
	OLS	F.E.	R.E.	OLS				
				np1	np2	npa1	npa2	npa3
	(i)	(ii)	(iii)	(iv)	(v)	(vi)	(vii)	(viii)
log R&D	0.32	0.20	0.38	0.26	0.03	0.22	0.07	0.00
	(16.63)	(3.66)	(14.39)	(9.26)	(1.87)	(6.29)	(4.15)	(-0.38)
K	0.02	0.23	0.03	0.03	0.01	0.05	0.02	0.01
	(2.07)	(2.36)	(2.27)	(2.04)	(2.61)	(3.02)	(3.18)	(1.29)
diversity	0.83	0.44	0.55	0.45	0.38	0.42	0.50	0.00
	(15.26)	(8.66)	(12.18)	(3.74)	(11.22)	(2.45)	(13.21)	(-0.09)
pat	0.15			0.35	0.07	0.36	0.10	0.02
	(3.73)			(4.32)	(3.02)	(4.02)	(3.58)	(0.53)
industry dummies	yes			yes	yes	yes	yes	yes
country dummies	yes			yes	yes	yes	yes	yes
constant	-1.10		-1.24	-0.71	0.19	-0.50	0.01	1.13
R^2	0.66	0.91	0.91	0.50	0.31	0.42	0.39	0.24
Adjusted R^2	0.65	0.88	0.91	0.47	0.28	0.37	0.37	0.05
Sample	967	967	967	434	533	316	651	118

Table 13': OLS, Fixed (F.E.) and Random (R.E.) effects estimation t-statistics between brackets Dependent variable: log(number of patents)								
	OLS	F.E.	R.E.	OLS				
				np1	np2	npa1	npa2	npa3
	(i)	(ii)	(iii)	(iv)	(v)	(vi)	(vii)	(viii)
log R&D	0.41	0.18	0.43	0.28	0.05	0.23	0.10	0.00
	(20.56)	(3.11)	(14.71)	(9.88)	(2.89)	(6.59)	(5.71)	(-0.35)
K	0.02	0.27	0.04	0.03	0.01	0.05	0.02	0.01
	(2.75)	(2.70)	(2.74)	(2.09)	(3.09)	(3.08)	(3.73)	(1.31)
adjusted diversity	0.30	0.07	0.14	0.24	0.13	0.24	0.17	-0.02
	(6.45)	(1.78)	(3.79)	(2.02)	(4.98)	(1.43)	(5.53)	(-0.49)
pat	0.23			0.36	0.10	0.36	0.14	0.02
	(5.33)			(4.39)	(3.97)	(4.04)	(4.87)	(0.52)
industry dummies	yes			yes	yes	yes	yes	yes
country dummies	yes			yes	yes	yes	yes	yes
Constant	-1.39		-1.33	-0.66	0.13	-0.44	-0.09	1.14
R^2	0.59	0.90	0.90	0.49	0.18	0.41	0.26	0.24
Adjusted R^2	0.58	0.86	0.90	0.46	0.15	0.36	0.23	0.05
Sample	967	967	967	434	533	316	651	118
columns (i) to (iii) total sample np1: firms with more than 10 patents np2: firms with less or 10 patents npa1: firms with more than 20 patents npa2: firms between one to 20 patents npa3: firms between 10 to 20 patents pat: dummy variable, one if firm has patented in the past, zero otherwise								

Tables 14 and 15 present OLS estimations of the determinants of the number of patents. Those tables try to estimate the value of technological diversification on innovation by sector or geographic location of the firm. In Table 14, the industry dummy variables have been multiplied by the technological diversification vector. Column (i) illustrates that sectors where it is specially important diversification are recreation and automotive. An increase of 10% of technological diversity, will increase an 8% the number of patents in all sectors and additional it will increase an 13% in this sector, for the automotive sector, the number of patents will increase additionally in 4% although this effect is weaker. Column (ii) shows the similar results when the country dummies are not included. Columns (iii) and (iv) report the same estimation without the diversity variable. Those columns suggest that technological diversification is an important factor to promote innovation in all sectors, specially in electronics, recreation, food and beverages, automotive, and electrical.

In Table 14, the country dummy variables have been multiplied by the technological diversification vector. Column (i) indicates that technological diversification is specially important to promote innovation in France, Germany and Netherlands. An increase of 10% in the technological diversification of any firm will induce an increase of the number of patents of 5% approximately. If the firm is French, additionaly it will increase the number of patents of 6%. If the firm is German, the additional increase will be 6% as well. Columns (iii) and (iv) show the OLS estimation when the diversity variable is not included in the regression. The results suggest that technological diversification is important for almost all countries in order to promote innovation.

Table 14: OLS estimation of determinants of patents t-statistics between brackets Dependent variable: log(no. patents)				
	(i)	(ii)	(iii)	(iv)
log R&D	0.31	0.34	0.31	0.34
	(15.71)	(18.35)	(15.84)	(18.41)
k	0.01	0.02	0.02	0.02
	(1.91)	(2.34)	(1.97)	(2.43)
diversity	0.83	0.70		
	(2.22)	(1.86)		
I1*diversity	0.13	0.24	0.94	0.92
	(0.35)	(0.63)	(14.48)	(14.36)
I2*diversity	0.22	0.36	1.03	1.05
	(0.58)	(0.96)	(12.06)	(12.34)
I3*diversity	-0.04	0.04	0.77	0.73
	(-0.11)	(0.11)	(9.34)	(9.04)
I4*diversity	0.06	0.20	0.87	0.89
	(0.15)	(0.52)	(8.10)	(8.38)
I5*diversity	1.31	1.34	2.12	2.03
	(2.90)	(3.00)	(7.90)	(7.97)
I6*diversity	-0.12	-0.02	0.69	0.67
	(-0.3)	(-0.05)	(6.54)	(6.45)
I7*diversity	-0.14	-0.01	0.68	0.68
	(-0.36)	(-0.03)	(7.71)	(7.74)
I8*diversity	0.31	0.40	1.12	1.09
	(0.81)	(1.04)	(10.13)	(10.05)
I9*diversity	0.40	0.55	1.22	1.24
	(1.07)	(1.45)	(13.15)	(13.45)
I10*diversity	-0.06	0.07	0.75	0.76
	(-0.15)	(0.18)	(5.29)	(5.27)
I11*diversity	0.24	0.37	1.06	1.05
	(0.62)	(0.94)	(8.09)	(8.15)
I13*diversity	0.06	0.11	0.86	0.80
	(0.14)	(0.28)	(6.42)	(5.95)
I14*diversity	-0.24	-0.15	0.57	0.54
	(-0.64)	(-0.39)	(5.42)	(5.14)
I15*diversity	0.00	0.12	0.81	0.81
	(-0.01)	(0.29)	(4.72)	(4.70)
Country dummies	yes	no	yes	no
constant	-1.13	-1.11	-1.14	-1.11
R^2	0.67	0.66	0.67	0.66
Adjusted R^2	0.66	0.65	0.66	0.65
Sample	967	967	967	967
See sector definitions in Table 1				

Table 15: OLS estimation of determinants of patents t-statistics between brackets Dependent variable: log(no. patents)				
	(i)	(ii)	(iii)	(iv)
log rd	0.31	0.32	0.31	0.32
	(15.82)	(17.24)	(15.86)	(17.31)
k	0.01	0.01	0.01	0.01
	(1.76)	(1.91)	(1.33)	(1.49)
diversity	0.49	0.48		
	(1.74)	(1.74)		
France*diversity	0.66	0.67	1.14	1.15
	(2.31)	(2.37)	(15.62)	(15.83)
Germany*diversity	0.68	0.69	1.15	1.16
	(2.42)	(2.43)	(15.63)	(16.25)
Greece*diversity	-0.50	-0.33	-0.08	0.09
	(-0.55)	(-0.36)	(-0.09)	(0.10)
Italy*diversity	0.34	0.39	0.82	0.87
	(1.15)	(1.33)	(7.78)	(8.32)
Spain*diversity	0.58	0.51	1.05	0.97
	(0.54)	(0.46)	(1.00)	(0.91)
Sweden*diversity	0.25	0.22	0.72	0.69
	(0.84)	(0.74)	(6.31)	(6.04)
UK*diversity	0.26	0.22	0.74	0.70
	(0.92)	(0.78)	(11.59)	(11.33)
Netherlands*diversity	0.57	0.57	1.05	1.04
	(1.95)	(1.93)	(10.03)	(10.15)
Finland*diversity	0.24	0.19	0.71	0.66
	(0.83)	(0.67)	(6.80)	(6.33)
Austria*diversity	0.08	0.02	0.56	0.50
	(0.23)	(0.06)	(2.78)	(2.48)
Belgium*diversity	0.34	0.37	0.82	0.85
	(1.15)	(1.25)	(7.13)	(7.68)
Denmark*diversity	0.44	0.44	0.91	0.92
	(1.44)	(1.45)	(6.45)	(6.62)
Industry dummies	yes	no	yes	no
constant	-0.85	-0.99	-0.83	-0.97
R^2	0.67	0.66	0.67	0.66
Adjusted R^2	0.66	0.65	0.66	0.65
Sample	967	967	967	967

In order to try to determine the robustness of the results, Tables 16 and 16' show the fixed and random effect estimation of equation (2) when the sample is divided in different subgroups depending on the number of patents the firm applies for. As in the estimation of the determinant of R&D, fixed and random effects estimations do not suggest an important effect of technological diversification on patent activity, specially in the subgroups analysys, with the exception of firms with few patents (for firms with less than twenty patents, the relationship is significant although the value of the estimated parameter is small). This result can be done because technological diversity is a very stable variable whose standard deviation is very small, that is, it is almost a constant in the period analyzed. Those results suggest that firms that small firms that diversified in the technological base seem to profit more from this effect than firms with many patents.

Table 16: Fixed (F.E.) and Random (R.E.) effects estimation t-statistics between brackets Dependent variable: log(number of patents)										
	Fixed Effects					Random Effects				
	np1	np2	npa1	npa2	npa3	np1	np2	npa1	npa2	npa3
	(i)	(ii)	(iii)	(iv)	(v)	(vi)	(vii)	(viii)	(ix)	(x)
log R&D	0.12	0.14	0.14	0.22	-0.10	0.27	0.05	0.24	0.11	0.00
	(1.96)	(1.87)	(1.85)	(2.74)	(-0.95)	(7.00)	(2.30)	(5.07)	(4.35)	(-0.24)
K	0.26	0.04	0.20	0.17	0.21	0.04	0.01	0.04	0.01	0.01
	(2.26)	(0.29)	(1.68)	(1.33)	(1.43)	(1.71)	(1.26)	(1.42)	(1.44)	(1.36)
diversity	0.23	0.32	0.06	0.38	-0.04	0.35	0.35	0.19	0.43	0.01
	(1.73)	(7.06)	(0.30)	(7.73)	(-0.53)	(3.15)	(10.22)	(1.18)	(11.19)	(0.34)
constant						-0.31	0.20	0.08	-0.02	1.10
R^2	0.86	0.61	0.82	0.68	0.64	0.86	0.58	0.81	0.61	0.60
Adjusted R^2	0.82	0.35	0.77	0.51	0.13	0.86	0.58	0.81	0.61	0.59
Sample	434	533	316	651	118	434	533	316	651	118

Table 16': Fixed (F.E.) and Random (R.E.) effects estimation t-statistics between brackets Dependent variable: log(number of patents)										
	Fixed Effects					Random Effects				
	np1	np2	npa1	npa2	npa3	np1	np2	npa1	npa2	npa3
	(i)	(ii)	(iii)	(iv)	(v)	(vi)	(vii)	(viii)	(ix)	(x)
log R&D	0.11	0.11	0.12	0.21	-0.09	0.27	0.07	0.24	0.14	0.00
	(1.74)	(1.40)	(1.56)	(2.46)	(-0.84)	(7.08)	(2.90)	(4.97)	(5.15)	(-0.15)
K	0.28	0.05	0.22	0.20	0.21	0.05	0.01	0.05	0.02	0.01
	(2.44)	(0.34)	(1.85)	(1.48)	(1.44)	(1.86)	(1.56)	(1.51)	(1.78)	(1.40)
adjusted diversity	0.02	0.07	-0.15	0.07	-0.07	0.15	0.10	0.01	0.11	-0.01
	(0.19)	(1.99)	(-0.79)	(1.78)	(-0.96)	(1.39)	(3.76)	(0.04)	(3.51)	(-0.17)
constant						-0.24	0.17	0.22	-0.10	1.10
R^2	0.86	0.55	0.82	0.64	0.65	0.85	0.53	0.81	0.62	0.60
Adjusted R^2	0.81	0.26	0.77	0.44	0.14	0.85	0.52	0.81	0.62	0.59
Sample	434	533	316	651	118	434	533	316	651	118
np1: firms with more than 10 patents np2: firms with less or 10 patents npa1: firms with more than 20 patents npa2: firms between one to 20 patents npa3: firms between 10 to 20 patents										

If R&D expenditures are unreported by firms, the regressor would be subject to measurement error. In that case, it can be interested to estimate equation (2) using instrumental variables. Tables 17 and 18 show Negative Binomial and OLS estimation of innovation with sales and debt as instrumental variables of R&D expenditures.

Table 17: Binomial negative estimation
z-statistics between brackets
Dependent variable: number of patents

	(i)	(ii)
sales	0.43	0.51
	(18.82)	(22.30)
debt	-0.37	-0.41
	(-3.87)	(-4.27)
K	0.49	0.59
	(4.22)	(4.91)
diversity	1.77	
	(12.28)	
adjusted diversity		0.72
		(5.36)
pat	0.47	0.60
	(4.29)	(5.29)
constant	-8.06	-9.62
Log likelihood	-3505	-3559
Sample	888	888

Both Tables 17 and 18 are consistent with previous results. The estimates imply that an increase in the available knowledge pool and in the technological diversification of the firm would increase the innovative activity of the firm. Since the estimated parameters are very similar to previous ones, it does not seem that there are very important differences due to possible problems to unreported R&D expenditures.

Table 18: OLS estimation t-statistics between brackets Dependent variable: log(no. patents)		
	(i)	(ii)
sales	0.33	0.43
	(14.54)	(18.28)
debt	-0.12	-0.16
	(-2.55)	(-2.93)
K	0.01	0.01
	(0.72)	(1.20)
diversity	0.89	
	(15.98)	
adjusted diversity		0.33
		(6.79)
pat	0.12	0.20
	(2.95)	(4.33)
constant	-1.71	-2.32
R^2	0.65	0.58
Adjusted R^2	0.64	0.56
Sample	965	965

Taken together, all the results provide support for the thesis that technological diversified firms, those that have a higher available knowledge pool and that have patented in the past are more innovative.

5 Conclusions and comments

This investigation examines the effects of the technological diversity of firms on R&D expenditures and innovation. An econometric analysis based on panel data of 544 European firms from 1995 to 2000 shows evidence of the positive relationship between diversity on the firm's patent portfolio and R&D and innovation. Scherer (1984) was pioneering in the analysis of firm production structure and productivity, also Cohen and Malerba (1995) and Audretsch and Feldman (1999) find a strong relationship between technological diversity and innovation at the industry level. They find that at the industry and at the firm level innovation is lower when the company is specialized within narrow industries than when it is diversified across a complementary set of industries. However a possible problem of their measure of innovative diversity is that is based on terms of employment activity or in the firm's variety of products and not on the technological activities undertaken by the firms. This paper tries to explicitly measure the firm technological diversity using patent data. To do that is has been followed the Jaffe's approach (1986, 1988 and 1989) of calculating the firm patent portfolio. Diversity is measured as one minus the Herfindahl index of concentration of the technological portfolio of the firm. The results of this section suggest that more diversified firms have more incentives to invest in R&D activities and to innovate. These results are consistent with the Scherer's idea that the more diversified firms can have a higher profit of their own research, since part of this new knowledge can be incorporated not only to the science-base of this innovation but also to the different projects that the company undertakes, it could be seen as a spillover effect among different activities inside of the firm. Therefore, it seems that technological diversification, together with financial constraints are important for innovation and both R&D expenditures and R&D intensity.

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