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EXPLAINING THE PROPENSITY TO PATENT: SOME EVIDENCE FROM ITALIAN MANUFACTURING FIRMS

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SOMMARIO

We study the determinants of patent probability (innovation output) in Italian manufacturing firms from 2003 to 2010. Empirical evidence, based on a large dataset, shows that firms' propensity to patent is significantly affected by intangible assets, ownership concentration, financial resources and additional firm attributes. Intangible activity is strongly significant with a positive marginal effect. On the other hand, an increase in independence – that is a decrease in ownership concentration – would decrease the probability of successful patent applications. Both external finance and self-financing are statistically significant with positive sign, but internal finance is relatively more important in both coefficient and level of significance in explaining the probability of successful patent application. As to the other explanatory variables, age and size are strongly significant with a positive marginal effect. Some differences arise when large firms and SMEs are examined separately, but the analysis as a whole would confirm the importance of internal funds for successful patent applications. The empirical findings are strengthened also when the analysis takes into account the endogeneity problem.

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1. Introduction

Innovation is at the basis of future economic growth, competitiveness, employment and ecological sustainability. As in the modern economy it emerges from a continuous interaction between firms, suppliers, buyers, and external environment at sectoral, regional and national levels, there is an increasing need to understand both the driving forces and the consequences of innovation and technological change.

Several studies have been possible and significant progress has been made on applied research on innovation thanks to publicly available, internationally comparable and reliable micro-data on innovation process. However, the choice among different innovation indicators is not trivial since they are characterised by strengths and weaknesses at the same time (Kleinknecht et al. 2002).

We choose patents as output measure of innovation in order to investigate the determinants of the innovative performance in Italian manufacturing firms from 2003 to 2010. We are aware that the patent indicator misses non-patented inventions and innovations, but it is one of the best measure in absence of specific, more detailed, information from questionnaires. Moreover, patent data are available over long time periods and they show only minor disturbances by occasional changes of patent laws.

Although many studies in the field of economics of innovation try to explain how intangibles, ownership structure, finance, firm attributes, market characteristics and location influence innovation, this paper contributes to the existing literature on innovation output in several ways. First, while the majority of empirical analyses focuses on one, or at most a few, intangible at a time, in this study a comprehensive account of intangibles is adopted to explicitly evaluate their impact on firms' innovative performance. Second, in previous studies several criteria or measures have been adopted to describe ownership structure and its characteristics. The majority of works uses a dichotomous approach by classifying firms as family and non-family firms on the base of a minimum equity stake of the founding family and/or additional criteria. This research, on the contrary, employs an indicator which allows us to investigate the effect of different degrees of firms' independence on patent probability. In this context, it also extends empirical evidence on European countries. Finally, our analysis explicitly deals with the endogeneity problem by applying a "Special Regression" to study the probability of a firm's successful patent application. It is one of the first paper applying the recent Lewbel's approach to deal with the endogeneity problem in binary choice models.

The paper is organized as follows. Section 2 briefly illustrates the related literature. Section 3 specifies the relevant variables for the empirical investigation and illustrates some descriptive statistics. Section 4 presents the model and the empirical evidence on the determinants of innovation output probability. Section 5 concludes.

2. Innovative performance and its determinants: a summary of related literature

The great relevance of R&D activity on firms' innovation output has been widely claimed in academic research. More recently, however, the "system approach" to innovation (Carlsson et al., 2002) and the "open-innovation mode" (Chesbrough, 2003) argue that the innovation process is much less R&D-centric than the standard linear model suggests. Not only is R&D a crucial innovation input, but also other non-R&D intangibles through which firms can introduce both technological and non-technological innovations: training, software development, company reputation and branding, design of products and services, organization or business process improvements[3].

Intangible assets as a whole are particularly important for today's knowledge-based economy. The role of intangibles as value and growth creators, indeed, is accepted among economists, investors and managers.

[3] For a review and alternative intangibles' categories, see Choong (2008) and Montresor and Vezzani (2014).

Thus, intangible assets are a principal driver of firms' competitiveness (Lev, 2001; Nakamura, 2001), but they also increase opportunities for workers and significantly affect labor productivity, economic growth and, in turn, the economic well-being of both local communities and nations (Marrocu et al., 2011; National Research Council, 2009; Corrado et al. 2009; Corrado et al., 2006). These are strategic investments in the long-run growth path of individual companies and of the economy as a whole. For this reason, intangibles are increasingly seen by policy makers as essential for the sustained economic health of the economy. The OECD Project "New sources of growth: Knowledge-based capital" (OECD, 2013) and the European Commission initiative "Design for Innovation" are important examples of the current policy focus on non-physical assets as a whole.

Given the importance of knowledge-based capital, it would be desirable to take account of all intangible assets that firms can use to a different extent for their innovative activity. For this reason, differently from previous empirical analyses which focus on one or at most a few intangible at a time, we adopt a comprehensive account of intangibles.

Additional researches aim to measure how firm performance correlates with intangible assets management and discuss microeconomic and macroeconomic implications of intangibles and their role in global economies by analyzing a range of policy-relevant topics such as how intangibles are created and used by firms, how intangibles contribute to growth, the variety and scale of emerging markets in intangibles, what the governments' role should be in supporting markets and promoting investments in intangibles (Corrado el a., 2006; Corrado et al., 2009). Our goal here is to explicitly evaluate the impact of intangible assets on firms' innovation output.

Another branch of literature investigates the effect of family ownership on firms' investment policy and innovative performance. In previous studies, several criteria or measures have been adopted to describe ownership structure and its characteristics. The majority of works uses a dichotomous approach by classifying firms as family and non-family firms on the base of a minimum equity stake of the founding family and/or additional criteria. For example, Anderson and Reeb (2003) require a minimum ownership stake of the founding family larger than 0%, Villalonga and Amit (2006) use both 0% and 20% as thresholds, Barontini and Caprio (2005) require a minimum founding family ownership stake of 51% for a firm to be classified as a family firm. Andres (2011) categorizes a firm as a family business if a) the founder and/or family members hold more than 25% of the voting shares or if the founding family or b) the founding family is represented on either the executive or the supervisory board (if they own less than 25% of the voting rights). A more sophisticated measure to quantify family influence along several dimensions is proposed in Astrachan et al. (2002), but it requires detailed data, usually gathered through questionnaires. For this reason, it is hard to implement in large dataset. Despite previous works, we use a discrete Independence Indicator which allows to investigate the effect of different degrees of ownership concentration on successful patent applications.

This work also adds to a recent literature that investigates whether differing access to various sources of finance affects innovative performance. Specifically, the analysis aims at evaluating also the impact of finance on patent probability.

As is observed by Cohen *et al*. (2000) and Lanjouw and Schankerman (2004), international patent protection requires sometimes significant filing costs, so the application for it signals both the availability of internal funds and expectations of substantial economic value for the invention. Moreover, whereas R&D activity as such is typically risky, requiring risk-sharing and external funding, patent application and enforcement, though costly, is less uncertain.

In this context, our research also aims at investigating whether finance affects innovative performance (Amore et al. 2013; Campello et al. 2010; Duchin et al. 2010; Leary 2009; Lemmon and Roberts 2010).

Finally, many studies in the field of economics of innovation try to explain how firm attributes, market characteristics and location influence innovation output (Cohen, 1995; Cohen and Klepper, 1996; Johansson

and Loof, 2008). For an overview see Kleinknecht and Mohnen (2002). Apart from intangibles, ownership structure and financial resources, additional firm attributes that are expected to influence the type and the intensity of a firm's innovation activity include size, age, capital assets, export propensity and history. Innovation intensity also depends on market structure and differs considerably among industrial sectors (Cohen, 1995). The same strand of literature focuses on the so-called "proximity-based communication externality" and investigates how a firm's innovation output is affected by the characteristics of the urban region where the firm is located. The assumption is that large urban regions have higher rates of innovation, facilitate information and knowledge flows, increase a firm's collaboration with research organizations, competitors, suppliers and customers (Glaeser, 1999; Feldman and Audretsch, 1999; Fujita and Thisse, 2002; Johansson and Quigley, 2004).

For these reasons, this paper also considers firm attributes, industry classification and market concentration in the analysis of the determinants of innovation.

3 Preliminary definitions and descriptive statistics

3.1 Variable Definitions and Data Sources

This study aims at investigating the determinants of Italian manufacturing firms' patenting activity. As a first step, a clear definition of the relevant variables is needed.

Given the complexity of technological knowledge capital, innovation is neither directly observable nor easily predictable, which makes it difficult to detect the main results of technological innovation (Nelson 2003; Lanjouw and Schankerman 2004). Scholars therefore increasingly use patent counts and other patent-related indicators to gauge innovative performance (Chava et al. 2013; Amore et al. 2013; Pederzoli et al. 2013; Motohashi 2011; Benfratello et al. 2008; Griliches 1990). Accordingly, we analyze the determinants of firms' "patent probability". We examine all manufacturing companies that have been granted at least one patent between 2003 and 2010. The firms that have patented successfully are extracted from the Bureau van Dijk's *Orbis* database; in this database, patents are those filed with the European Patent Office (EPO). The identities of firms obtaining patents, which are not available in the Amadeus database, have been kindly supplied by Bureau van Dijk. Patent data are then matched with the Amadeus accounting database using the companies' *BvD ID Number,* which ensures the precision of the match, with no need to harmonize firms' names[4].

Intangible activity, financial and ownership variables are mainly based on firms' accounting data taken from the *Amadeus* database published by Bureau van Dijk.

Since firms may finance innovation projects either through external financial sources, as bank loans and other debt contracts, or through internal sources, such as cash flow, an important step of the analysis consists in defining an appropriate empirical measure of external and internal finance. By external financing we mean funds not generated internally (not self-financing). Therefore, we measure external finance (*EXTF*) as the ratio of loans, long-term debt and trade credit to total assets[5]. As usual in the literature, we use cash-flow as indicator of internal financial resources and measure internal finance (*INTF*) as the ratio of cash flow to total assets.

To characterize the degree of independence of a company with regard to its shareholders, we use the BvD Independence Indicator (*IND*) included in the BvD Ownership Database.

[4] The matching procedure has shown a very good accuracy score of 87.13% (11,478 of 13,173 companies with patents were perfectly matched).

[5] The variable *Loans* includes: Bonds, Convertible Bonds, Due to Banks, Due to other lenders. The variable *Long Term Debt* includes: Bonds beyond 12 months, Convertible bonds beyond 12 months, Due to banks beyond 12 months, Due to other lenders beyond 12 months (Amadeus – User Guide, Correspondence Table for Italian companies).

The BvD Independence Indicators are noted as A, B, C, D and U, with further qualifications.

Indicator A identifies *Independent Companies* and it is attached to any company with known recorded shareholders none of which having more than 25% of direct or total ownership (see Appendix A.1 for details on calculated total percentage).

This is further qualified as A+, A or A-:

- A+: companies with 6 or more identified shareholders (of any type) whose ownership percentage is known;
- A: as above, but includes companies with 4 or 5 identified shareholders;
- A-: as above, but includes companies with 1 to 3 identified shareholders.

The logic behind these qualifiers is that the probability of having missed an ownership percentage over 25% is the lowest when the greatest number of shareholders is known, so that the company's degree of independence is more certain.

The qualification A+ is also attributed to A companies in which the sum of direct ownership links (all categories of shareholders included) is over 75%. Which means that those companies cannot have an unknown shareholder with 25% or more and can thus not be identified with an Independence Indicator other than A.

Note that BvD also gives an A- notation to a company that is mentioned by a source (Annual Report, Private Communication or Information Provider) as being the ultimate owner of another company, even when its shareholders are not mentioned.

As it can be noted from the above definitions, the qualifications "+" or "-" do not refer to a higher or a lower degree of independence but to the *degree of reliability* of the Indicator that is attributed.

Indicator B is attached to any company with a known recorded shareholder none of which with an ownership percentage (direct, total or calculated total) over 50%, but having one or more shareholders with an ownership percentage above 25%.

The further qualification as B+, B and B- is assigned according to the same criteria relating to the number of recorded shareholders as for indicator A.

The qualification B+ is also attributed to B companies in which the summation of direct ownership percentages (all categories of shareholders included) is 50.01% and higher. Indeed, this means that the company surely does not qualify under Independent Indicator C (since it cannot have an unknown shareholder with 50.01% or higher).

Indicator C is attached to any company with a recorded shareholder with a total or a calculated total ownership over 50%. It identifies the so called "*società detenute indirettamente a maggioranza*".

The qualification C+ is attributed to C companies in which the summation of direct ownership percentage (all categories of shareholders included) is 50.01% or higher. Indeed, this means that the company surely does not qualify under Independent Indicator D (since it cannot have an unknown direct shareholder with 50.01% or higher).

The C indicator is also given to a company when a source indicates that the company has an ultimate owner, even though its percentage of ownership is unknown.

Indicator D is allocated to any company with a recorded shareholder with a direct ownership of over 50%. It identifies the so called "*società detenute direttamente a maggioranza*".

Indicator U is allocated to companies that don't fall into the categories A, B, C or D, indicating an unknown degree of independence.

For computational reasons, the BvD Independence Indicator has been transformed into a discrete variable taking values from 0 (*IND*=U) to 9 (*IND*=A+) (see Table 2 for a distribution of firms by Independence Indicator).

3.2 Descriptive Statistics

In this paragraph, we report some descriptive statistics. The basic universe of the sample is the set of firms in the Italian manufacturing sectors with positive intangible assets over the 2003-2010 years. We find a higher percentage of patenting firms than those found in other empirical researches due to the analysis being focused on manufacturing sectors - typically characterized by a strong patenting activity (see Lotti and Marin 2013 for a comparison with non-manufacturing sectors) - and on firms within such sectors with positive intangible activity. Moreover, while we use the full Aida database other authors use the Top Aida database (see, for example, Lotti and Marin 2013).

Table 1 reports the distribution of patenting and non-patenting firms by sectors (following the NACE Rev.2 primary codes), size and geographical location.

The data confirm that innovation intensity differs considerably between industrial sectors (Cohen, 1995). Patenting firms are present in all kinds of sectors, but they prevail in capital intensive sectors like the manufacture of electrical equipment, manufacture of basic metals, manufacture of basic pharmaceutical products and pharmaceutical preparations. On the other hand, patenting firms are hardly present in Manufacture of tobacco products, Printing and reproduction of recorded media, Manufacture of beverages, Manufacture of paper and paper products and other low-tech sectors. Following the classification adopted by Archibugi (2001) and distinguishing among high-tech sectors (HT), medium-high-tech sectors (MHT), medium-low-tech sectors (MLT) and low-tech sectors (LT), we find an overall evidence that firms in high-tech sectors account for 36.34% of all patenting activity, medium-high-tech firms seldom contribute 9.7% of filings. The non-patenting firms are mainly active in low-tech and medium-low-tech sectors (40.12% and 34.21% respectively).

Looking at the geographical location, the data show that patent holding firms are heavily concentrated in the Centre and North of the country. As expected, the patenting firms are more concentrated in more developed Italian regions: the highest rate is in Lombardy (33.18%), followed by Veneto (16.66%), Emilia Romagna (14.86%) and Piedmont (9.28%). This evidence would confirm the importance of the external environment for the knowledge creation process. The proximity afforded by locating in large and developed urban areas creates an advantage for firms by facilitating information and knowledge flows (Johansson and Loof, 2008).

Table 1 also reports the distribution of patenting firms by size class. The firm size is measured in terms of annual turnover, which allows to split the sample on the basis of the threshold values reported in the Commission Recommendation 96/280/EC (updated in 2003/361/EC of May 6, 2003): small firms (€2 mln <turnover<€10 mln); medium-sized firms (€10 mln <turnover<€50 mln); large firms (turnover>€50 mln). In the paper we carry out the analysis by considering small and medium enterprises (SMEs) together. Looking at the size distribution of firms, the small and medium enterprises represent the highest percentage of both patenting and non-patenting firms, but the differences between the two groups of firms are less pronounced than those regarding industrial characteristics and geographical location.

Table 1- Distribution of firms by sectors (NACE Rev.2 primary codes), size and location (% values)

		Patenting Firms	Non-Patenting Firms
10	Manufacture of food products (LT)	2.61	8.85
11	Manufacture of beverages (LT)	0.33	1.74
12	Manufacture of tobacco products (LT)	0.01	0.05
13	Manufacture of textiles (LT)	2.73	5.01
14	Manufacture of wearing apparel (LT)	2.05	5.08

15	Manufacture of leather and related products (LT)	1.36	3.05
16	Manufacture of wood and of products of wood and cork, except furniture; manufacture of articles of straw and plaiting materials (LT)	1.74	2.66
17	Manufacture of paper and paper products (LT)	0.97	2.67
18	Printing and reproduction of recorded media (LT)	0.26	0.48
19	Manufacture of coke and refined petroleum products (MLT)	4.43	4.33
20	Manufacture of chemicals and chemical products (HT)	1.93	0.67
21	Manufacture of basic pharmaceutical products and pharmaceutical preparations (HT)	7.93	5.73
22	Manufacture of rubber and plastic products (MLT)	3.91	6.42
23	Manufacture of other non-metallic mineral products (MLT)	2.27	3.26
24	Manufacture of basic metals (MLT)	17.19	20.08
25	Manufacture of fabricated metal products, except machinery and equipment(MLT)	5.75	3.24
26	Manufacture of computer, electronic and optical products (HT)	7.08	4.75
27	Manufacture of electrical equipment (MHT)	24.95	12.34
28	Manufacture of machinery and equipment nec (HT)	2.77	1.60
29	Manufacture of motor vehicles, trailers and semi-trailers (MHT)	1.40	1.36
30	Manufacture of other transport equipment (HT)	4.09	4.13
31	Manufacture of furniture (LT)	4.25	2.50
32	Other manufacturing (LT)	0.01	0.00
		100.00	*100.00*
	Large firms	42.21	44.68
	SMEs	57.79	55.32
		100.00	*100.00*
	Centre-North	94.09	89.31
	South	5.01	10.69
		100.00	*100.00*
	N. of firms	10318 10125	31894 30292

Source: Based on Amadeus and Orbis data.

Table 2 shows the distribution of patenting and non-patenting firms by Independence Indicator. The Italian manufacturing sector is characterized by very high levels of ownership concentration. Indeed, 59.17% of patenting firms and 53.63% of non-patenting firms are characterized by an Independence Indicator equal to D, indicating a recorded shareholder with a direct ownership of over 50%. In these organizations, which usually identify family businesses, one or more shareholders have a direct control of the company (the so called "*società detenute direttamente a maggioranza*").

Next, more than 30% of patenting firms are characterized by an Independence Indicator equal to B, thus they have one or more shareholders with an ownership percentage above 25%, but none of which with a direct, indirect or total control over 50%.

Only 7% of the firms included in the sample can be considered independent companies, with an Independence Indicator equal to A. In these cases, there is no shareholder with a direct or total ownership over 25% (the so called "*società indipendenti*").

Table 2 - Patenting and Non-patenting firms by Independence Indicator (% values)

Independence Indicator	*value*	*All firms*	*Patenting firms*	*Non-Patenting firms*
U	0	1.67	1.24	1.82
D	1	55.02	59.17	53.63
C	2	0.72	1.05	0.61
C+	3	0.00	0.00	0.00
B-	4	0.00	0.00	0.00
B	5	35.16	31.61	36.35
B+	6	0.00	0.00	0.00
A-	7	0.00	0.00	0.00
A	8	7.43	6.93	7.60
A+	9	0.00	0.00	0.00
		100.00	*100.00*	*100.00*

Source: Based on Amadeus and Orbis data.

Table 3 illustrates some descriptive statistics about intangible assets over total assets (*IA*), Independence Indicator (*IND*), external financial resources over total assets (*EXTF*), internal finance over total assets (*INTF*), age and size of the firms. Size is expressed in terms of annual turnover.

Overall, the results on the univariate analysis show that patenting firms are, on average, older, larger, characterized by higher intangible activity and lower independence (higher ownership concentration) than non-patenting firms.

Table 3 - Summary Statistics

		Patenting Firms			
Variable	Obs	Mean	Std. Dev.	Min	Max
IA	10582	0.168	0.250	0.01	1.00
IND	9657	2.747	2.328	0	8
EXTF	4468	0.223	0.167	0	1.684
INTF	6246	0.058	0.052	-0.771	0.403
Age	10893	24.697	16.119	0	133
Size	10895	29401.68	210498.9	-51	1.77e+07
		Non-Patenting Firms			
Variable	Obs	Mean	Std. Dev.	Min	Max
IA	31414	0.137	0.218	0.01	0.645
IND	28826	2.973	2.380	0	8
EXTF	9184	0.231	0.167	-0.129	1.084
INTF	17752	0.055	0.049	-0.426	0.563
Age	31639	20.721	15.129	0	117
Size	31646	13417.03	106566.6	-365	7984961

Source: Based on Amadeus and Orbis data.

4 Regression Analysis

4.1 Model and empirical results

To estimate firms' patent probability we use a logistic regression model. Under the logistic specification, the dependent variable is dichotomous, equal to 1 if the firm had at least one successful patent application between 2003 and 2010 period and 0 if not.

In formal terms:

$$p_i = \Pr(PATENTS_i = 1) = F(x_i\,\beta) \quad [1]$$

where p_i is the probability that the dependent variable *PATENTS*=1 for firm *i*, $F(\cdot)$ is the logistic cumulative distribution function, x_i is the set of explanatory variables presumed to affect p_i, β are the regression coefficients.

More specifically, our regression takes the following form:

$$p_i = \Pr(PATENTS_i=1) = F(\beta_0+\beta_1 IA_i+\beta_2 IND_i+\beta_3 EXTF_i+\beta_4 INTF_i+\beta_5 Age_i+\beta_6 Size_i+\beta_7 X_i) \quad [2]$$

$i = 1 \ldots n$ where *i* is the *i*th firm.

The predictor *IA* indicates the ratio of Intangible Assets to total assets.

The Independence indicator *IND* captures the ownership concentration.

INTF and *EXTF* indicate the ratio of internal and external resources to total assets respectively.

We also include age, size and additional firm attributes. The vector X, in particular, includes a measure of market power, sector and regional dummies.

To take account of the market power, we consider a traditional structural measure of market concentration based on market shares. In particular, this study includes the concentration ratio C_4 which measures the total market share of the four largest firms in each manufacturing sector included in the analysis and it is comparable from sector to sector.

Note that we consider all manufacturing companies that have been granted at least one patent between 2003 and 2010, but we do not know the exact date in which the patent has been granted. Thus, all the explanatory variables are entered as the firm-level average for 2003-2010 years.

The logistic regression has been expressed in its exponential form, i.e., in a non-linear form[6] as follows:

$$p_i = \frac{\exp(\beta_0 + \beta_1 IA_i + \beta_2 IND_i + \beta_3 EXTF_i + \beta_4 INTF_i + \beta_5 Age_i + \beta_6 Size_i + \beta_7 X_i)}{1+\exp(\beta_0 + \beta_1 IA_i + \beta_2 IND_i + \beta_3 EXTF_i + \beta_4 INTF_i + \beta_5 Age_i + \beta_6 Size_i + \beta_7 X_i)} \quad [3]$$

Table 4 shows the logistic regression results, in exponential form, for the entire sample. Since the parameters are not directly interpretable as marginal effects, these have been explicitly calculated. Moreover, as the first-order conditions are non-linear with respect to parameters, a numerical approximation is used, producing convergence after 17 reiterations. The maximized value of the log-likelihood function is -8106.74.

The *p*-value on the LR chi-square allows to reject the null hypothesis that all the coefficients are simultaneously equal to zero, so the model as a whole is statistically significant. To avoid the risk of multicollinearity, the bivariate correlation test has been run, showing no linear relation among variables. To further corroborate this result, we computed the *tolerance*, an indicator of how much collinearity a regression analysis can tolerate, and the variance inflation factor, an indicator of how much of the inflation of the standard error could be due to collinearity. For our variables, both measures were close to 1, excluding any multicollinearity.

Analyzing the estimates (Table 4), as expected intangible activity is strongly significant with a positive marginal effect. Firms with substantial intangible assets are 2.31 times ($e^{0.84}$) as likely to increase their patenting activity as those without.

On the other hand, an increase in independence – that is a decrease in ownership concentration – would decrease the probability of successful patent applications. In line with Andres (2011) and Anderson and Reeb

[6] The disadvantage of using a linear form would be that the maximum likelihood estimates are expressed in a logit scale and therefore are not directly interpretable as probability.

(2003), we find that ownership concentration, which usually characterize the Italian family businesses, fosters the innovative performance by presumably aligning the incentives between management and shareholders in long term investment decisions, like innovation projects.

We reach a number of interesting empirical findings concerning the influence on patenting exerted by financial channels and other variables. Both internal and external financial resources are statistically significant at the 1% level and with the expected positive sign; but the coefficient of internal funding is significantly higher. Specifically, a 1% increase in external finance increases the probability of successful patents application by 0.09%, while the same increase in internal financial resources results produces an increase of 0.45%. In terms of the odds ratios, holding the other variables constant, raising internal finance by one unit increases the odds ($p_i/1\text{-}p_i$) of patenting by 731% [(8.31-1)*100]. In other words, firms with substantial internal financial resources are 8.31 times ($e^{2.117}$) as likely to increase their patenting activity as those without. Analogously, firms with more access to external finance are 1.59 times ($e^{0.466}$) as likely to patent as firms with severe external financial constraints. In short, access to finance is very significant for innovative performance, but internal finance seems to be economically more important. Because patenting costs are relatively high and most of them must be paid up front, only firms with sufficient liquidity can cover them. The innovative performance of Italian manufacturing firms seems to be significantly affected by the availability of internally generated funds. The highly concentrated family holdings and their long presence in the firm imply that these firms are tempted to rely on internal sources of finance when funds for patents applications are needed. External debt financing might be considered too risky, also due to the increased default probability.

As to the other explanatory variables, age is significant at the 1% level with a positive sign, presumably indicating the importance of experience for innovation and, to some extent, the presence of learning economies. For an age increase equal to 1 (a unit measure in our analysis) the odds ($p_i/1\text{-}p_i$) of patenting increase by 3% [(1.03-1)*100][7].

As we expect, firm size is significant with a positive marginal effect. In terms of the odds ratios, for a turnover increase of €100,000 Euros (one unit) the odds of patenting increase by 14%, holding the other variables constant. "… Larger firms may patent more often simply because they are bigger and employ patent lawyers and other personnel solely for this purpose (Bound et al. p.42)".

The industry concentration rate is significant in explaining successful patent applications at the 5% level. Sector and regional dummies are almost all significant at the 1% level.

Table 4 - Logistic Regression - Estimation results, All Firms

Dependent variable: $PATENTS_i$

	Coefficient β	*Marginal effects* *dy/dx*	*Odds ratio* e^{β}
IA	0.840***	0.153***	2.317***
	(0.054)	(0.009)	
IND	-0.047***	-0.008***	0.953***
	(0.005)	(0.000)	
EXTF	0.466***	0.099***	1.59***
	(0.131)	(0.027)	
INTF	2.117***	0.449***	8.31***

[7] Note that also age-squared has been initially included in the logistic model to capture non-linear effects. It would have been significant with a negative sign, indicating decreasing returns to scale. The variable has been eliminated from the model since Lewbel' approach - used to handle endogeneity - does not allow to include it since we consider age as special regressor.

	(0.418)	(0.088)	
Size	0.139***	0.029***	1.15***
	(0.021)	(0.004)	
Age	0.031***	0.006***	1.031***
	(0.004)	(0.000)	
C_4	0.101**	0.036**	1.10**
	(0.087)	(0.002)	
Sector Dummies	included	included	
Regional Dummies	included	included	
constant	8.855***		
	(0.870)		
	Log-likelihood: -8106.74		
	Pseudo R^2 = 0.10		
	LR chi2(49)= 1611.33		
	Prob > chi2= 0.000		
	N = 14011		

Notes: Robust Standard Errors in parenthesis. Significance levels: *10%; **5%; ***1%. Sector and Regional Dummy variables, unreported to save space but available on request, are significant at 1% level.

Some differences arise when large firms and SMEs are examined separately (Table 5), but the analysis as a whole would confirm the importance of intangible assets, internal funds and size for successful patent applications.

Specifically, the Independence Indicator still enters with negative sign, but it is not significant in explaining large firms' patent probability. More than 73% of large companies, indeed, have a recorded shareholder with a direct ownership of over 50%. While external finance is not significant in explaining large firms' patenting activity, internal finance and size would appear to be the most relevant predictors of patent probability. Increasing internal finance by 1% (one unit) increases the odds ($p_i/1$-p_i) of large firms' patenting by 160% [(17.06-1)*100], holding the other variables constant. Thus, the availability of internal resources and skilled R&D staff, more likely to be found in larger firms, would be relatively more important than the other factors.

When the analysis is applied to SMEs, the Independence Indicator enters significantly with negative sign. Moreover, the findings confirm that both internal and external financial resources are statistically significant at the 1 % level with the expected positive sign, but internal finance is relatively more important in both marginal effect and level of significance. While an increase in external finance by 1% raises the probability of successful patent application by 0.06%, the same increase in internal finance increases it by 0.24%. In terms of odds ratios, increasing internal finance by 1% (a unit) raises the odds ($p_i/1$-p_i) of SMEs' patenting by 238% [(3.38-1)*100], holding the other variables constant. Therefore, SMEs with greater internal financial resources are 3.38 times as likely to increase their patenting as those with limited internal resources. Analogously, SMEs with higher access to external finance are 1.38 times as likely to patent.

In brief, internal funding is strongly significant in explaining Italian manufacturing firms' patent probability. For large firms, it is the sole channel that explains successful patent applications, for SMEs self-financing is relatively more important than external finance.

With respect to the other explanatory variables, size is significant for both large firms and SMEs, indicating the likely presence of skilled R&D staff; age is significant only for SMEs. The industry concentration rate, instead, is significant only for large firms. Finally, sector and regional dummy variables are significant at 1% level.

Table 5 - Logistic Regression - Estimation results, Large Firms and SMEs

Dependent variable: $PATENTS_i$

	LARGE			*SMEs*		
	Coefficient β	*Marginal effects*	*Odds ratio* e^{β}	*Coefficient* β	*Marginal effects*	*Odds ratio* e^{β}
IA	2.844***	0.707***	17.19***	0.442***	0.078***	1.556***
	(1.037)	(0.257)		(0.087)	(0.015)	
IND	-0.017	-0.004	0.983	-0.029***	-0.005***	0.970***
	(0.023)	(0.006)		(0.006)	(0.001)	
EXTF	0.438	0.108	1.54	0.321**	0.064**	1.38**
	(0.393)	(0.097)		(0.136)	(0.028)	
INTF	2.836**	0.705**	17.06**	1.219***	0.242***	3.38***
	(1.191)	(0.293)		(0.461)	(0.091)	
Size	0.037**	0.009**	1.04**	3.551***	0.708***	35.08***
	(0.015)	(0.004)		(0.199)	(0.039)	
Age	0.017	0.004	1.01	0.030***	0.006***	1.03***
	(0.011)	(0.002)		(0.004)	(0.000)	
C_4	0.082**	0.019**	1.08**	0.035	0.008	1.03
	(0.023)	(0.008)		(0.021)	(0.006)	
Sector Dummies	included	included		included	included	
Regional Dummies	included	included		included	included	
constant	8.64***			8.225***		
	(1.670)			(0.982)		
	Log-likelihood: -880.379			Log-likelihood: -6625.476		
	Pseudo R^2 = 0.11			Pseudo R^2 = 0.11		
	LR chi-square(49)= 227.48			LR chi-square(49)= 1642.73		
	Prob > chi-square= 0.000			Prob > chi-square= 0.000		
	N = 1429			N = 12119		

Notes: Robust Standard Errors in parenthesis. Significance levels: *10%; **5%; ***1%. Sector and Regional Dummy variables, unreported to save space but available on request, are significant at 1% level.

To have a complete picture, we estimate the patenting probability associated to the average Italian manufacturing firm – that is when all variables are at their means - by assuming similar conditions to those of 2003-2010 period (Table 6). The empirical evidence shows that, under the assumption of no major changes compared to previous years, the probability of successful patents applications for the average Italian manufacturing firm is 0.237.

We have also estimated the patent probability at the mean values of the predictors assuming similar conditions to those prevailing in 2003-2010. The predicted probability that the representative Italian manufacturing firm will obtain a patent in the future is p_i=0.48 for large firms and p_i=0.231 for SMEs, again indicating a relatively higher propensity to patent for larger firms.

Table 6 Representative Italian manufacturing firm and patent probability

	Means	
IA	0.144	
IND	2.91	
EXTF	0.229	$P_i = \Pr(y_i = 1) = 0.237$
INTF	0.056	
AGE	21.72	
SIZE	17510.79	

Source: own elaboration

4.2 Dealing with endogeneity

Previous works on innovative performance and ownership structures, as well as studies on innovation and financial resources do not explicitly deal with the endogeneity problem. To overcome the potential endogeneity of the regressors, we use Lewbel's approach to handling such problems for binary choice models (Lewbel 2004; Dong and Lewbel 2012; Lewbel at al. 2012). Lewbel's special regression requires one exogenous continuous variable with a large support that contains zero. For our case, a natural candidate as special regressor is age which is characterized by a relatively higher standard deviation and can assume value of zero. We consider the main predictors as endogenous, while as set of instrumental variables we consider regional dummies. The special regression reported in Table 7 confirms both the significance and the relative importance of the explanatory variables included in the logistic regression. The marginal effects of the financial variables on patent probability are even higher than in the logistic model.

Note that the main empirical evidence is also confirmed for large companies and SMEs.

Table 7 - Special Regression – Marginal effects

Dependent variable: PATENTS$_i$			
	All firms	*LARGE*	*SMEs*
IA	0.811***	0.888*	0.445***
IND	-0.097***	-0.019**	-0.032***
EXTF	0.399***	0.361	0.095**
INTF	0.628***	0.844**	0.481***
Size	0.002**	0.009*	0.016**
Age			
C_4	0.042**	0.039**	0.002
Sector Dummies	included	included	included
Regional Dummies	included as IV	included as IV	included as IV
	Wald chi2(34) = 423.82 Prob > chi2= 0.000 *N* = 12268	Wald chi2(34) = 52.02 Prob > chi2= 0.000 *N* = 1305	Wald chi2(34) = 30.93 Prob > chi2= 0.000 *N* = 10963

Notes: Robust Standard Errors in parenthesis. Significance levels: *10%; **5%; ***1%. Sector and Regional Dummy variables, unreported to save space but available on request, are significant at 1% level.

4.3 Validation of the Model

To evaluate our model, we computed the percentage of correct classifications, which gives us the percentage of correct predictions. The model predicted positive responses for 2,214 observations, of which 1,281 were

correctly classified (i.e., PATENTS=1), while the other 933 were incorrectly classified because the observed response was negative (Table 8). Likewise, negative responses were predicted for 11,797 observations, of which 8,416 were correctly classified (PATENTS=0). Overall, around 70% of predictions are correctly classified.

When we split the sample according to firms' size, we find that 65.6% of predicted patent probability is correctly classified for large firms and 72.2% for SMEs.

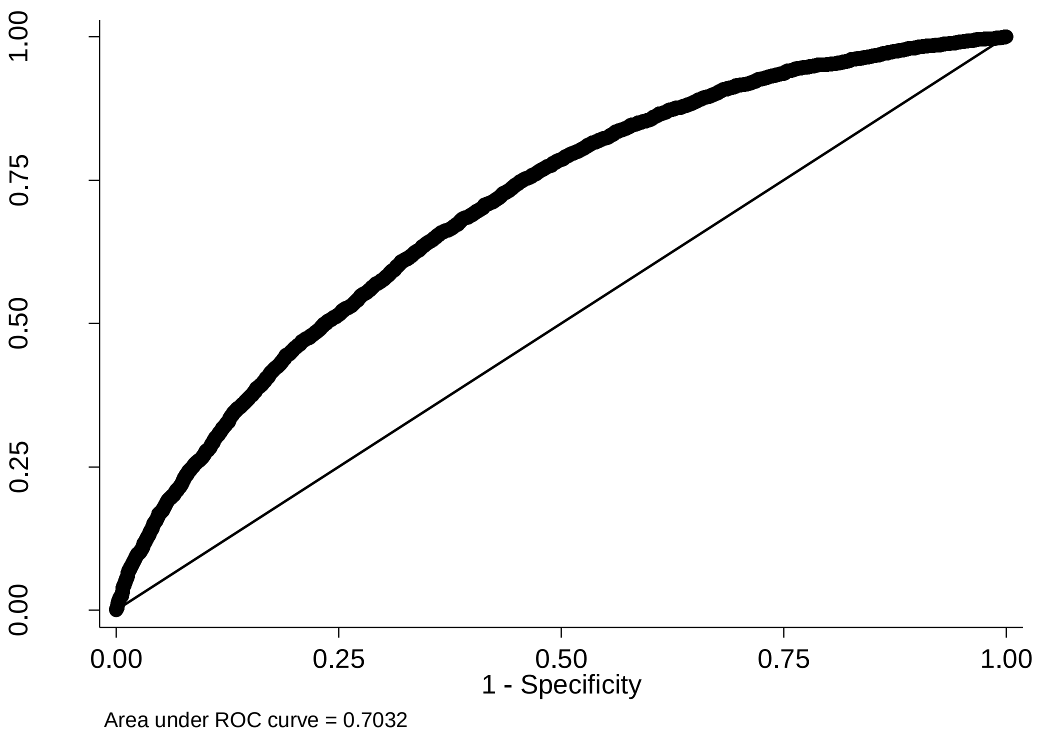
Table 8 Prediction of the model

Classified	*D*	*~D*	*Total*
+	1281	933	2214
-	3381	8416	11797
Total	4662	9349	14011
Correctly classified			69.21%

Notes: Classified + if predicted Pr(D) >= 0.5.

We further assessed the model's accuracy of classification using a receiver operating characteristic (ROC) curve (Figure 1). The results suggest that our model is a good fit with the data. A large area under the ROC curve indicates that the model can accurately predict the value of an observation's response; the discrimination is outstanding, with the relevant area larger than 0.7.

Figure 1- ROC Curve – All firms



Source: own elaboration

Finally, we checked for any specification error using the linktest (Table 9), which suggests that the model is not misspecified.

The idea behind linktest is that if the model is properly specified, one should not find any other statistically significant predictors, except by chance. The linktest uses the linear predicted value (_hat) and linear predicted value squared (_hatsq) as predictors to reconstruct the model. Since the variable _hat is a

statistically significant predictor, the model is not misspecified. On the other hand, if our model is properly specified, _hatsq should not have much predictive power. And in fact _hatsq is not significant, showing that no relevant variables have been omitted and the equation is correctly specified.

The control for specification error indicates that our model is not misspecified even when large firms and SMEs are separately analyzed.

Table 9 - Specification error test

patents	*Coef.*	*Std. Err.*	*z*	*P>z*
		All firms		
_hat	0.948	0.026	35.56	0.000
_hatsq	-0.038	0.042	-1.68	0.067
_cons	0.011	0.025	0.05	0.963
		Large Firms		
_hat	0.998	0.078	12.71	0.000
_hatsq	0.067	0.069	0.98	0.329
_cons	-0.037	0.070	-0.53	0.597
		SMEs		
_hat	1.044	0.049	21.12	0.000
_hatsq	0.026	0.024	1.09	0.274
_cons	0.002	0.028	0.08	0.936

Source: own elaboration

5 Conclusions

We study the determinants of patent probability (innovation output) in Italian manufacturing firms from 2003 to 2010.

Empirical evidence, based on a large dataset, shows that firms' propensity to patent is positively and significantly affected by intangible assets, ownership concentration, financial resources and additional firm attributes.

As expected, intangible activity as a whole is strongly significant with a positive marginal effect. Also other non-R&D intangibles through which firms can introduce both technological and non-technological innovations (training, software development, company reputation and branding, design of products and services, organization or business process improvements) are crucial innovation inputs.

On the other hand, an increase in independence – that is a decrease in ownership concentration – would decrease the probability of successful patent applications. Ownership concentration, which usually characterizes the Italian family businesses, would foster the innovative performance by presumably aligning the incentives between management and shareholders in long term investment decisions, like innovation projects.

Moreover, both the internal and external financial resources are statistically significant with the expected positive sign, but the coefficient of internal funding is significantly higher. Specifically, firms with substantial internal financial resources are 8.31 times as likely to increase their patenting activity as those without; firms with more access to external finance are 1.59 times as likely to patent as firms with severe external financial constraints. Thus, access to finance is very significant for innovative performance, but internal finance seems to be economically more important. Because patenting costs are relatively high and most of them must be paid up front, only firms with sufficient liquidity can cover them.

In short, the innovative performance of Italian manufacturing firms seems to be significantly affected by the availability of internally generated funds. The highly concentrated family holdings and their long presence in the firm imply that these firms are tempted to rely on internal sources of finance when funds for patents applications are needed. External debt financing might be considered too risky, also due to the increased default probability.

As to the other explanatory variables, age is strongly significant with a positive sign, presumably indicating the importance of experience for innovation and, to some extent, the presence of learning economies. Firm size is significant with a positive marginal effect. Larger firms may patent more often because they employ patent lawyers and other personnel solely for this purpose.

Some differences arise when large firms and SMEs are examined separately, but the analysis as a whole would confirm the importance of internal funds for successful patent applications.

The empirical findings are strengthened also when the analysis explicitly deals with the endogeneity problem.

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Appendix

A.1 Notes on Direct/Total Ownership in Aida and Independence Indicator

The *Ownership Database* intends to track control relationships rather than patrimonial relationships. This is why, when there are 2 categories of shares split into *Voting/Non voting shares*, the percentages that are recorded are those attached to the category *Voting shares*.

Direct Ownership

A link indicating that entity A owns a certain percentage of Company B is referred to as a direct ownership link.

Indirect Ownership

It is possible that a source gives both a direct and an indirect percentage. BvD makes the summation of the direct and indirect percentages and notes it as Total. For the sake of simplicity, the indirect figures are not recorded in the BvD Ownership Database.

Total Ownership

In some cases the information source indicates that entity A has a total stake in Company B without specifying the path through which the ownership is held. So, BvD computes the *Calculated Total Percentage*.

More specifically, to enhance the distinction between companies directly owned from those that are indirectly owned by a shareholder with more than 50%, BvD has decided to check whether companies with no recorded shareholder of more than 50% of direct ownership have some of their direct shareholders controlled by the same entity at the first or at a higher level. The concept of control follows the IFRS prescriptions according to which an entity (company, individual, etc.) controls a company when it owns more than 50% of the ownership.

If two minority direct shareholders are controlled by a third minority direct shareholder or by a same entity at a higher level, BvD creates a Calculated Total Link between the subject company and the controlling company and calculates a total percentage by making the sum of the direct percentages of all minority direct shareholders controlled by the same controlling company. This process is based on the concept of percentage of control as opposed to the concept of percentage of interest.

The Calculated Total Percentage of the controlling company is used to define the Independence Indicator (a company with an Independence Indicator A or B could change to an Independence Indicator D if this percentage is higher than 50%) but it will never be displayed as a shareholder.

This is mainly due to 2 reasons :

- even if the scope of the BvD ownership database is very wide, BvD cannot absolutely assert that all the existing links are recorded in the database. More importantly, since certain ownership structures can be very complex, trying to evaluate a controlling power could be misleading.
- BvD cannot associate this Calculated Total percentage to a correct validity date because it results from information valid at different dates.

Note that specific rules are applied for particular cases. Specifically, a company may report having at least one recorded shareholder with an interest in the company over a certain percentage (>X%).

If this percentage is under 25%, as we do not know the exact percentage of ownership, it is difficult to determine the level of independence. For such companies, specific rules are applied :

- If only one shareholder is reported to own over X% (and X=<25), then it is clear that we cannot determine if the shareholder has control or not so we assign the independence indicator U;
- If several shareholders are known, no one with more than 25% but with perhaps several reported to own over X% (X=<25), it is still difficult to determine the level of control and we also assign the independence indicator U;
- In only one case, we will still assign A+ : when the remaining unknown direct percentage added to the percentage of any shareholder reported to own over X% is lower to 25%. This means no one of those shareholders, even if they would own the remaining unknown percentage, will have more than 25% and change the independence indicator to B.