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"THE DRIVING FORCES OF PATENTING ACTIVITY IN ITALY"

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Abstract

This paper aims at studying the determinants of patenting activity in Italian manufacturing firms from 2006 to 2013. The firms with successful patent applications are extracted from the Bureau van Dijk's *Orbis* database, where patents are those filed with the European Patent Office. Patent data are then matched with the Bureau van Dijk's *Amadeus* accounting database through the companies' *BvD ID* number. Our empirical findings show a close association between ownership concentration and innovative performance. Specifically, an increase in ownership concentration would increase the probability of successful patent applications, but at decreasing returns to scale. The propensity to patent is also significantly affected by the amount of intangible assets, financial resources and additional firm attributes. Intangible activity is strongly significant with a positive marginal effect. 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. Age and size are strongly significant with a positive marginal effect suggesting the presence of learning economies and internal economies of scale. Some differences arise when large firms and SMEs are examined separately, but the analysis as a whole would confirm the importance of ownership concentration and internal funds for successful patent applications.

Keywords: Innovation, Patents, Ownership, Firm attributes, Logit, Special Regression

JEL Classification: C130, D22, K00, L60, O340

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).

In spite of an international debate on whether today's patent regime leads to more innovation (or not) and numerous researchers supporting the need to abolish or fix them (see Boldrin and Levine 2012; The Economist 8th august 2015), the patent indicator is still one of the best measure in absence of specific, more detailed, information on innovation activity from questionnaires. Moreover, patent data are available over long time periods and they show only minor disturbances by occasional changes of patent laws. Thus, we use patents as output measure of innovation and

investigate the determinants of patenting activity in Italian manufacturing firms from 2006 to 2013. The firms that have patented successfully are extracted from the Bureau van Dijk's *Orbis* database, while additional accounting data are taken from the Bureau van Dijk's *Amadeus* database.
This paper contributes to the existing literature on the driving forces of innovation in several ways. With reference to the corporate governance literature, the majority of works uses a dichotomous approach by classifying companies as independent or non-independent and family or non-family firms on the base of a minimum equity stake of the founding family and/or additional criteria. This research, instead, employs an indicator which allows to investigate the effect of different degrees of firms' ownership concentration on patent probability. Thanks to the information reported in the ownership database included in *Amadeus*, we are able to build an accurate indicator of different levels of control characterizing a company. Moreover, this paper provides a comprehensive analysis of the impact of firm-specific resources and capabilities on patenting activity by relating to the overall and most recent branches of scientific literature. Finally, with reference to methodology, 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 rest of 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: Related Literature

Several studies in the field of economics of innovation aim at explaining the determinants of firms' innovative behavior, defined in different ways in different contexts of analysis, by observing different phenomena at the level of the country, the industry or the firm.
A first branch of literature focuses on national innovation systems (Nelson, 1993) and analyses country-specific institutional factors and the quality of their interactions to explain endogenous sources of innovation (Edquist, 1997; Freeman & Soete, 1997; Lundvall, 1992).
Another line of research characterizes the industrial organization literature which considers industrial structure and its dynamics as significant factors affecting technological change (Acs & Audretsch, 1987; Scherer, 1990; Sutton, 1998). These works mainly focus on size and concentration of industries, market power, market entry and exit, the degree of vertical or horizontal integration and diversification of products.
Contemporary literature working on the analysis of innovation performance at firm level include both corporate governance and strategic management literature. This study, based in microdata, is more connected to these last two branches if literature, shown in detail below.

2.1 Corporate governance literature

A relevant branch of the recent literature focuses on the impact of corporate governance - which determines a set of mechanisms for the allocation of resources and the distribution of their returns- on firms' innovative performance.
Many empirical studies aim at explaining firms' innovative behavior - defined in different ways in different contexts of analysis - by focusing on ownership structure. While there is a general consensus on the relevance of the ownership structure for determining a firm's investment strategy, empirical evidence on the effect of ownership concentration on firm innovation is conflicting. While some studies show positive relationship (Lee and O'Neill 2003; Hosono, Tomiyama, & Miyagawa, 2004), others found negative (Yafeh & Yosha, 2003) or neutral associations (Francis & Smith, 1995). Choi et al. (2012) even find that ownership concentration has not a significant effect on firm technological innovation performance; however, some ownership types do have a positive effect. In this regard, it is desirable and crucial to enlarge empirical examinations in the context of advanced economies, emerging markets and less developed countries, in order to verify if and to what extent some clearer association exist between ownership structure and innovation performance. This study contributes to the existing literature by offering additional evidence from Italian manufacturing firms.
In contrast to theoretical considerations regarding investment models (Petersen and Rajan, 1992), several empirical studies show that family ownership is associated with higher firm performance. Andres (2011) provides evidence for more efficient investment decisions and fewer agency conflicts and information asymmetries in family firms. Family ownership would align the incentives between management and shareholders and this advantage seems to outweigh the possible disadvantages in terms of access to external capital (Anderson and Reeb, 2003).
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 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 an ownership indicator which allows to investigate the effect of different degrees of ownership concentration on successful patent applications.

2.2 Strategic management literature

The strategic management literature focuses on firm-specific resources and capabilities as important sources of innovation heterogeneity and performance. Contemporary literature on economics of innovation, in particular, focuses on additional firms' characteristics such as intangible activity, access to finance, firm attributes, market characteristics and firm location, to explain different innovation propensity of firms.
Some researchers investigate how firm performance correlates with intangible assets management and discuss microeconomic and macroeconomic implications of intangible activities 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).
Also from a microeconomic perspective, intangible assets as a whole play an increasing role in applied researches. While the great relevance of R&D activity on firms' innovation output has been widely claimed in academic research, more recently, the new "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[1].
Hence, the intangible assets as a whole play an important role in today's knowledge-based economy. The role of intangibles as value and growth creators is accepted among economists, investors and managers. In this context, 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 in our analysis.
Our research also adds to the literature evaluating the impact of finance on innovative activity (Amore et al. 2013; Campello et al. 2010; Duchin et al. 2010; Leary 2009; Lemmon and Roberts 2010). This study, indeed, investigates whether differing access to various sources of finance affects the probability of successful patent applications.
As it 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 its enforcement, though costly, is less uncertain.
Finally, an important strand of literature focuses on the influence of firm attributes, market characteristics and location on innovation output (Cohen, 1995; Cohen and Klepper, 1996; Johansson and Loof, 2008; for an overview see Kleinknecht and Mohnen, 2002).
Firm attributes found to influence the type and the intensity of a firm's innovation activity usually include size, age, capital assets, export propensity and history.
Other studies focus on the so-called "proximity-based communication externality" and investigate 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). Several works, indeed, underline the importance of the interaction with the scientific community for firms' innovation activities, especially for patenting activity (Slaughter and Leslie, 1997; Feldman and Audretsch, 1999).

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

3 PRELIMINARY DEFINITIONS AND DESCRIPTIVE STATISTICS

3.1 Variable Definitions and Data Sources

As mentioned above, 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). Therefore, as mentioned in the introduction, scholars 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 focus on "patent probability" and examine all manufacturing companies that have been granted at least one patent between 2006 and 2013. The firms that have patented successfully are extracted from the Bureau van Dijk's *Orbis* database, where patents are those filed with the European Patent Office (EPO)[2]. 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[3].

To characterize the degree of independence of a company with regard to its shareholders, therefore its ownership concentration, we explicitly evaluate the percentage of ownership held by the main shareholder. Differently from dichotomous indicators, this allows to investigate the effect of different levels of control on successful patent applications. Note that, when there are two categories of shares split into voting/non voting shares, the percentages are computed considering only the category voting shares because the research focuses on control relationships rather than on patrimonial relationships.

Just for a descriptive analysis, we identify as *Independent Companies* those firms with known recorded shareholders none of which having more than 25% of direct[4] or total ownership.

An intermediate level of control characterizes those companies 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%.

We identify as indirectly majority-owned companies (the so called "*società detenute indirettamente a maggioranza*") those companies with a recorded shareholder with a total or a calculated total ownership over 50% [5].

Finally, directly majority-owned companies (the so called "*società detenute direttamente a maggioranza*") are those firms with a recorded shareholder with a direct ownership of over 50%.

With respect to total ownership, it is necessary to clarify that 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.

With reference to the other covariates, both financial variables and additional firms' characteristics are taken from the *Amadeus* database published by Bureau van Dijk.

We include intangibles as a whole and consider the ratio between intangible assets and total assets (*IA*). Intangible Assets, as a proxy for the intangible production factors, include R&D expenditure, copyrights, software, employee training, trademarks and the like.

Moreover, 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

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[2] The matching between the firms included in the Orbis database and the European Patent Register is carried out by Vadis [http://www.vadis.com], a company specialized in predictive modelling and data mining.

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

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

[5] Note that 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.

internally (not self-financing). Therefore, we measure external finance (*EXTF*) as the ratio of bank loans, long-term debt, external equity and trade credit to total assets[6].
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.
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).
Additional firm attributes are briefly described in paragraph 4.1.

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 2006-2013 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.
Table 1 reports the distribution of patenting and non-patenting firms by sectors, size and geographical location. Industrial sectors have been classified according to the NACE Rev.2 primary codes.
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. 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

[6] 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). Moreover, note that external equity has been defined - in accordance with Park and Pincus (2001) - as total common shareholders' equity less internal equity.

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	31894

Source: Based on Amadeus and Orbis data.

Table 2 shows the distribution of patenting and non-patenting firms by ownership concentration. 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 have 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 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. In these cases, there is no shareholder with a direct or total ownership over 25%.

These results are expected and coherent with country-level indicators of rule of law for governance measure.

Corporate Governance - defined as the legal system for investor protection from expropriation by “insiders” - plays an important role in determining firm valuation, efficient allocation of resources and ownership structures of firms (La Porta et al. 1998, 1999, 2000). Worldwide Governance Indicators (WGI) and the World Bank Doing Business Report (2015) show a very low position of Italy in the international ranking: rank 21/189, with a score of 67/100, considering the protection of minority investors; rank 147/189, with a score of 45.6/100, considering the enforcement of contracts.

Our descriptive findings would suggest an inverse relationship between ownership concentration and protection of minority investors in Italy.

Table 2 Patenting and Non-patenting firms by Ownership concentration (% values)

Ownership	All firms	Patenting firms	Non-Patenting firms
unknown ownership composition	1.67	1.24	1.82
with a recorded shareholder with a direct ownership of over 50%	55.02	59.17	53.63
with a recorded shareholder with a total or a calculated total ownership over 50%	0.72	1.05	0.61
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%	35.16	31.61	36.35
with known recorded shareholders none of which having more than 25% of direct or total ownership	7.43	6.93	7.60
	100.00	*100.00*	*100.00*

Source: Based on Amadeus and Orbis data.

Table 3 illustrates additional descriptive statistics on intangible assets over total assets (*IA*), external financial resources over total assets (*EXTF*), internal finance over total assets (*INTF*), age and size of the firms.
In brief, the overall results on the univariate analysis show that patenting firms are, on average, older, larger, characterized by higher intangible activity and 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
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
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 2006 and 2013 period and 0 if not.
In formal terms:

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

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:

$$p_i = \Pr(PATENTS_i=1) = F(\beta_0+\beta_1 OWN_i+\beta_2 OWNsq_i+\beta_3 IA_i+\beta_4 EXTF_i+\beta_5 INTF_i+\beta_6 Age_i+\beta_7 Size_i+\beta_8 X_i)$$

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

The variable *OWN* captures the companies' ownership concentration, given by the percentage of ownership held by the main shareholder. It can take values from 0 to 1. We also include its squared value *OWNsq* to allow for possible non linearity in the patenting-ownership relationship, that is to verify if scale effects exist.
The predictor *IA* indicates the ratio of Intangible Assets to Total Assets.
INTF and *EXTF* indicate the ratio of internal and external resources to total assets respectively.
We also include firms' age and size, while the vector X includes a measure of market power, sector and regional dummies as additional control variables. To take account of the market power, we include 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 a dependent variable equal to 1 for all manufacturing companies that have been granted at least one patent between 2006 and 2013, 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 2006-2013 years (as in Beyer et al. 2012)
The logistic regression has been expressed in its exponential form, i.e., in a non-linear form[7] as follows:

$$p_i = \frac{\exp(\beta_0 + \beta_1 OWN_i + \beta_2 OWNsq_i + \beta_3 IA_i + \beta_4 EXTF_i + \beta_5 INTF_i + \beta_6 Age_i + \beta_7 Size_i + \beta_8 X_i)}{1 + \exp(\beta_0 + \beta_1 OWN_i + \beta_2 OWNsq_i + \beta_3 IA_i + \beta_4 EXTF_i + \beta_5 INTF_i + \beta_6 Age_i + \beta_7 Size_i + \beta_8 X_i)}$$

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.
LR chi-square (49) is the asymptotic version of the *F*-test for zero slopes. The *p*-value rejects 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.
The estimates show that an increase in ownership concentration – that is a decrease in independence – would increase the probability of successful patent applications. The variable *OWN*, indeed, enters significantly with positive sign, suggesting a driving force of ownership concentration in reducing agency conflicts (alignment benefits) and improving innovative capacity. In line with Andres (2011) and Anderson and Reeb (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. The literature on corporate governance indicates that one way to reduce the conflicts of interest that lead to agency costs is to increase the proportion of shares in the firm held by managers.
To allow for possible non linearity in the patenting-*OWN* relationship, we add the log of *OWN* squared to the regression. *OWNsq* enters significantly with negative sign, indicating decreasing returns to scale. This empirical result suggests that alignment benefits increase with ownership concentration, but at decreasing rate.
The empirical evidence as a whole shows that, as ownership concentration rises from very low levels, firm innovative performance improves but, as ownership continues to rise, firm performance falls off. Hence, at a first phase, ownership concentration benefits, in terms of potential lower costs of controlling managers (associated to a difference between managerial and shareholder interests) and/or lower costs of collective decision making (due to heterogeneity of interests among the owners) outweigh its potential costs in terms of risk bearing[8], and this would increase patent probability. As ownership becomes more concentrated, countervailing pressures realize so that the final result will not necessarily be a reduction of agency costs (Jensen and Meckling, 1976), with a consequent lower patent propensity.
With respect to the other covariates, 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.
We also reach a number of interesting empirical findings concerning the influence on patenting exerted by financial channels and other covariates. 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

[7] 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.
[8] For a detailed review of the costs of ownership, see Hansmann 2000.

other variables constant, raising internal finance by one unit increases the odds ($p_i/1-p_i$) 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, when accessible, might be considered too burdensome and risky.

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 ($p_i/1-p_i$) of patenting increase by 3% [(1.03-1)*100][9].

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. According to Bound et al. (1984, pag.42) "… larger firms may patent more often simply because they are bigger and employ patent lawyers and other personnel solely for this purpose". Hence, empirical findings as a whole would highlight the presence of some specialization and internal economies of scale.

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}**
OWN	0.047***	0.008***	1.048***
	(0.005)	(0.000)	
OWNsq	-0.002***	-0.000	0.998***
	(0.000)	(0.000)	
IA	0.840***	0.153***	2.317***
	(0.054)	(0.009)	
EXTF	0.466***	0.099***	1.59***
	(0.131)	(0.027)	
INTF	2.117***	0.449***	8.31***
	(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.

[9] 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 in paragraph 4.2 - does not allow to include it since we consider age as special regressor.

Some differences arise when large firms and SMEs are examined separately (Table 5), but the analysis as a whole would confirm the driving role of intangible assets, internal funds, ownership concentration and size for successful patent applications.
Specifically, the variable OWN still enters with positive sign, but it is less 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%. When the analysis is applied to SMEs, ownership concentration is significant at 1% level with positive sign and decreasing returns to scale.
With reference to financial variables, while external finance is not significant in explaining large firms' patenting activity, internal finance would appear to be one of the most relevant predictor of their patenting activity. Increasing internal finance by 1% (one unit) increases the odds (pi/1-pi) 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 we focus on SMEs, the findings show 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 (pi/1-pi) 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 and economies of scale; 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}**
OWN	0.072***	0.018***	1.075***	0.029***	0.005***	1.030***
	(0.017)	(0.004)		(0.005)	(0.000)	
OWNsq	-0.017	-0.004	0.983	-0.029***	-0.005***	0.971***
	(0.023)	(0.006)		(0.006)	(0.001)	
IA	2.844***	0.707***	17.19***	0.442***	0.078***	1.556***
	(1.037)	(0.257)		(0.087)	(0.015)	
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 Pseudo R^2 = 0.11 LR chi-square(49)= 227.48 Prob > chi-square= 0.000 N = 1429			Log-likelihood: -6625.476 Pseudo R^2 = 0.11 LR chi-square(49)= 1642.73 Prob > chi-square= 0.000 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 have also estimated the patent probability at the mean values of the predictors assuming similar conditions to those prevailing in 2006-2013. The predicted probability that the representative Italian manufacturing firm – that is when all variables are at their means - will obtain a patent in the future is p_i=0.48 for large firms and p_i=0.231 for SMEs, indicating a relatively higher propensity to patent for larger firms.

Finally, we compute the effect of the ownership concentration on patent probability for the representative firm (Table 6). The probability of successful patents application is equal to 0.21 for more independent firms. It increases to 0.35 when ownership concentration increases - that is when a recorded shareholder has a total or a calculated total ownership over 50% - then it decreases again suggesting an-inverted U relationship between ownership concentration and patent propensity.

Table 6 Effect of ownership concentration on (predicted) patent probability

Representative firm	with known recorded shareholders none of which having more than 25% of direct or total ownership	$Pr(y_i=1) = 0.22$
	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%	$Pr(y_i=1) = 0.21$
	with a recorded shareholder with a total or a calculated total ownership over 50%	$Pr(y_i=1) = 0.35$
	with a recorded shareholder with a direct ownership of over 50%	$Pr(y_i=1) = 0.257$
	unknown ownership composition	$Pr(y_i=1) = 0.172$

Source: own calculations.

4.2 Dealing with endogeneity

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). See paragraph A.1 in the Appendix for details on this methodology.

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 the variable *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.

Table 7 Special Regression – Marginal effects

Dependent variable: $PATENTS_i$			
	All firms	**LARGE**	**SMEs**
OWN	0.097***	0.019**	0.032***
OWNsq	-0.008**	-0.006	-0.002
IA	0.811***	0.888*	0.445***
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.

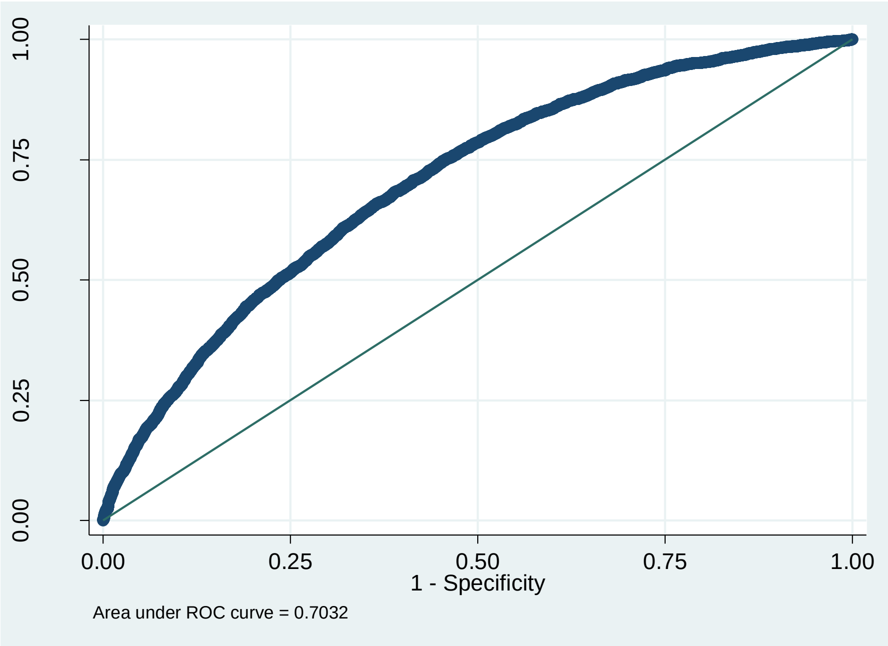
Table 8 Prediction of the model

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. 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).

Figure 1 ROC Curve – All firms



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

5 Conclusions

In this paper we study the driving forces of patenting activity in Italian manufacturing firms from 2006 to 2013.
Empirical evidence, based on a large dataset, shows that firms' propensity to patent is positively and significantly affected by ownership concentration, as well as intangible assets, financial resources and additional firm attributes.
Specifically, an increase in ownership concentration would increase 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. The alignment benefits, however, would increase with ownership concentration at decreasing returns to scale. Policy makers should be aware of the impact of corporate governance reforms on innovation performance in order to increase policies' effectiveness and success.
With reference to the other predictors, intangible activity as a whole is strongly significant with a positive and relevant marginal effect. Hence, 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.
Moreover, both the internal and external financial resources are statistically significant with the expected positive sign, but the impact of internal funding is significantly higher. In particular, 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 external 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, when accessible, might be considered too burdensome and risky.
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 ownership concentration and the availability 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 Special Regression Method for Binary Choiche Model

To handle the problem of endogeneity, the empirical econometric literature suggests the use of instrumental variables. However, the latter are often unavailable or too weak (Brown et al., 2014) and in same case it is an hard task to find good instruments that fit well with models. To circumvent this difficulty, we adopt an alternative approach proposed by Lewbel: the special regressor method (Lewbel, 2014, Lewbel et al. 2012, Dong et Lewbel, 2012). This methodology, which is based on earlier seminal work by the same author (Lewbel, 2000), is relatively easy to implement and relies on assumptions that are quite different from those required for maximum likelihood estimators. The special regressor approach does not impose restrictions on the model errors and does not require the relationship between the endogenous and exogenous regressors to be specified, but its consistency relies on the presence of one exogenous regressor that is conditionally independent of the model error, is continuously distributed, and has a large support. The special regressor thus provides a simple way of testing the validity of the modelling assumptions underlying more standard maximum likelihood approaches.
The special regressor approach proposed by Lewbel (2000) was designed in a broad context to improve the identification and estimation of parameters and their associated distributions in general threshold-crossing models such as the following binary decision model:

$$D = \mathrm{I}(\mathbf{X}'\boldsymbol{\beta}+\varepsilon \geq 0) \qquad (1)$$

where D represents the binary decision variable, the vector $\mathbf{X}$ includes all observable regressors, ε has a zero mean distribution, and I(.) is the indicator function taking the value one if the latent variable $\mathbf{X}'\boldsymbol{\beta}+\varepsilon$ is positive and zero otherwise. Traditional probit and logit models correspond to the case of ε following a normal and exponential distribution, respectively.
The special regressor model has the same form as model (1) but is rewritten so that one regressor V (that is called the special regressor) is separated from the other regressors $\mathbf{X}$ and its coefficient is normalised to one:

$$D = \mathrm{I}(\mathbf{X}'\boldsymbol{\beta}+V+\varepsilon \geq 0) \qquad (2)$$

The special regressor V must satisfy three fundamental conditions:
- V is continuously distributed and has a large support (i.e., V varies on a support that is as large as the support of $\mathbf{X}'\boldsymbol{\beta}+\varepsilon$);
- V is exogenous;
- $E(D|\,\mathbf{X},V)$ increases with V.

If some elements of $\mathbf{X}$ are endogenous, then the special regressor method requires instruments satisfying the following usual properties: $E(\mathbf{Z}'\varepsilon) = 0$ and $E(\mathbf{Z}'\mathbf{X})$ has full rank. The special regressor V should not be included in the set of instruments $\mathbf{Z}$ which implies that a suitable V should only affect the binary decision of interest, and not the endogenous (binary) variable. Further, note that only one special regressor is needed whatever the number of endogenous variables in the model.
The basic idea behind the special regressor approach is shortly described below (while we refer to Lewbel (2014) for additional details).
Define T as:

$$T = \frac{D - I(V \geq 0)}{f_{V|Z}(V|Z)}$$

where $f_{V|Z}(V|Z)$ denotes the conditional probability density function of V given $\mathbf{Z}$. Under the above assumption, it can be shown that $E(T \mid \mathbf{Z}) = E(\mathbf{X}'\boldsymbol{\beta}+\varepsilon \mid \mathbf{Z})$, assuming ε is independent of $V \mid \mathbf{Z}$ (Lewbel, 2014). It follows from the latter equality that $E(\mathbf{Z}\mathbf{X}')\boldsymbol{\beta} = E(\mathbf{Z}\,T)$ and so:

$$\beta = [E(XZ')E(ZZ')^{-1}E(Z'X)]^{-1}E(XZ')E(ZZ')^{-1}E(ZT)$$

which is the definition of a linear two-stage least squares regression of T on **X** using instruments **Z**. We describe below the steps to be followed to estimate and the parameters of interest **β** (see Dong and Lewbel 2012 for more insight about technical details) :

Step 0*:* *V* must be of mean zero; if not, one must first de-mean it.

Step 1*:* Run an Ordinary Least Squares (OLS) regression of *V* on (**X,Z**) and, for each observation *i*, compute the residuals as the difference between the observed V_i and its prediction: $\widehat{U}_i = V_i - (X'_{\hat{b}_X} + Z'_{\hat{b}_Z})$, where $\hat{b}_X$ and $\hat{b}_Z$ are the OLS estimated coefficients for variables in **X** and **Z**, respectively.

Step 2*:* Compute $\hat{f}_h$ as the non-parametric kernel estimator of the density *f* of $\widehat{U}$ and for each *I* compute the estimates $\hat{f}_i = \hat{f}(\widehat{U}_i)$. Note that such estimation requires a kernel *K*(.) and a bandwidth to be chosen. Alternatively, one may use the ordered data estimator proposed by Lewbel and Schennach (2007). See also Dong and Lewbel, 2012, for details.

Step 3*:* For each observation *i* construct:

$$\hat{T}_i = \frac{D_i - I(V_i \geq 0)}{\hat{f}_i}$$

Note that in this ratio the denominator can take very small values especially for large absolute values of $\widehat{U}_i$. As a consequence, some could have extremely large absolute values, which could induce large standard errors in the final two-stage least squares regression. Lewbel (2014) recommends either removing these extreme values for example using a trimming procedure.

Step 4*:* Compute $\widehat{\boldsymbol{\beta}}$ as the coefficient of a two-stage least squares regression of $\widehat{T}$ on **X** using instruments **Z.**

The estimation of the special regressor thus involves four steps that can be implemented relatively easily in most statistical software: a procedure is available in STATA (see Baum, 2012). Further, classical tests of instruments' validity can be applied at the final two-stage least squares regression knowing that $E(\mathbf{Z}\varepsilon) = E(\mathbf{Z}\tilde{\boldsymbol{\varepsilon}})$ with $\tilde{\boldsymbol{\varepsilon}} = T - \mathbf{X}'\boldsymbol{\beta}$, the error term of the Step 4 regression of on using instruments (see Dong and Lewbel, 2012).