Matthew effect, capabilities and innovation policy. The Argentinean case.

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Abstract

The objective of this paper is to analyze the process of allocation of public funds for innovation, in order to test the presence of Matthew effects. According to the literature, the Matthew effect refers to the impact on reputation of past accessing to public funds, which increases the probability of accessing in the present It explains why public agencies are prone to fund projects submitted by firms with past subsidized innovation projects. The dataset is made of 966 firms that accessed the Technological Argentinean Fund (in Spanish FONTAR), which is the main instrument to foster innovation, during 2007-2013 –around 3300 observations. It includes agricultural, manufacturer and service firms, with different sizes and from different regions. Results show that past access to FONTAR increases the probability of accessing in the present, thus confirming the Matthew effect. However, they show that firm's innovative capabilities and qualified human resources also explain the probability of accessing, which provides evidence regarding the presence and importance of a 'capability effect'. When firms are analyzed in terms of technological intensity, the Matthew effect is stronger among low-tech firms, while the share of qualified personnel –a traditional proxy of capabilities- has the highest impact among high-tech companies. These results suggest that once the firm entered the system, it remains with an active innovative behavior, not just because of the reputation effect or how easily they prepare and submit a project, but also because it has accumulated capabilities and sunk investments in the pursuit of a technological competitive advantage.

Key words: Matthew effect, persistence, capabilities, innovation policy

1. Introduction

The objective of this paper is to study the allocation of public funds for innovation, in order to analyze the high rates of persistence observed not only in Argentina but also in other countries with different levels of development (Aschhoff, 2009; Crespi, Maffioli, et al., 2011; Duguet, 2003; González et al., 2005; MINCyT, 2015a; Radicic et al., 2014; Tanayama, 2007). According to the literature, one of the main sources of persistence is the so called Matthew effect and refers to the reputation impact of past accessing on the selection process of the projects to fund. To the extent that public agencies do not have perfect information or the required capabilities to identify the best projects (whatever 'best projects' means), the fact that a firm had received a subsidy in the past positively impact on the evaluation of its present projects (Antonelli and Crespi, 2013a).

The relevance of the topic lies on its intended contribution to the debate regarding the selection of beneficiaries. From a 'picking the winners' position, the rate of persistence leads to wonder if the beneficiaries are the 'correct winners' in terms of the innovative process, the positive externalities, the economic impact, or any other indicator (Radicic et al., 2014). From a 'spread the seed' position, public agencies have difficulties identifying the best projects and the recurrence rate constitutes a steady equilibrium that not necessarily includes the 'winners' (Arora and Gambardella, 1997; David, 1994). In this case, the challenge is to maximize variety and minimize persistence in order to extend the number of funded projects. In both cases, a relevant aspect of public policy evaluation is the quantification of the persistence rate and the characterization of the persistent firms.

The database is made of 966 firms hat accessed the Argentinean Technological Fund (FONTAR) during the period 2007-2013 –around 3300 observations. The database includes all firms that accessed any of the FONTAR instruments –non-refundable grants, subsidize credits and tax refund- at least once, and provides information regarding innovation and research and development (R&D) investments, qualified human resources and sector of activity, besides the traditional economic and structural indicators such as sales, employment, location and age.

FONTAR is the main source of public funding for innovation at the firm level, in terms of both the number of instruments and the amount of the grants (Porta and Lugones, 2011). It is administered by the National Agency for Scientific and Technological Promotion, which depends on the National Ministry of Science and Technology and Productive Innovation (in Spanish, MINCyT). The Fund was established in 1992 and subsequently ratified and re-funded by the following governments - from the more neo-liberal to the most protectionist. The number of instruments of financing, the average level of grants, and the types of funded projects had a strong stimulus in 2003, when the economic crisis was overcome and a new model based on a strong public intervention was implemented. As a result, the number of beneficiaries and projects has increased significantly since 2003. FONTAR evaluations showed positive impacts in terms of additionality, national coverage and innovation results (López et al., 2010). Recent analyses regarding the allocation of funds show that each year about half of the beneficiaries are persistent firm and account for 60% of total allocation of funds, and half of them are newcomers and account for the remaining 40% (MINCyT, 2013).

In order to analyze persistence a dynamic random effect probit model was estimated, which tests the impact of being granted with a FONTAR fund in the past on the probability of accessing in the present –a state dependence probability. Methodologically speaking, the variables to use and the relationships to test have two types of endogeneity: one that arises from the correlation between the unobservable fixed effect of each firm and its observable characteristics, and another that results from the structure of autocorrelation in the error term. To tackle the first problem, the Mundlak-Chamberlain approach (Chamberlain, 1984; Mundlak, 1978) was used and the average value for a set of time-variant and economically relevant variables (sales and employment) was included. The second type of endogeneity was addressed with the Wooldridge solution and the initial condition was added to the estimation (Wooldridge, 2005).

Results show that firms which accessed public funds in the past have higher probabilities of accessing public funds in the present, thus confirming the Matthew effect. Once firm's characteristics are controlled, there is some inertia between past and present grants that can be explained by the impact of firm's reputation. This impact is higher among low-tech firms, possibly due to the characteristics of low-tech firms within the Argentinean productive structure, where large traditional companies explain the bulk of the level of employment and have high levels of influence on public opinion. It also could be a sign of the difficulties public offices face in terms of identifying viable technological projects among firms where the productive process is –by definition- based on mature technologies.

Results also show that firm's capabilities have a direct relationship with the probability of accessing public funds. Firms with higher levels of qualified personnel and a high-profile innovative behavior have higher chances of getting funded. Therefore, there are signs of capability effects, which are even higher among high-tech firms. In this regard, to the extent that these are on average younger and smaller firms, accessing to public funds seems to depend more on the firm's capabilities to identify relevant funding lines and properly developing and submitting a project rather than just having accessed in the past. Of course, results can also respond to the fact that these firms have projects with a longer time horizon and a larger time lag is required.

From an aggregated view, results seem to point that once firms entered the system of public funding of innovation they have higher probabilities of remain inside it, not just because of the reputation effect or how easily they prepare and submit a project, but also because they have accumulated capabilities and sunk investments in the pursuit of a technological competitive advantage. Of course, this also poses questions regarding the continuity of that innovative behavior without public support, the capability of public funds to trigger new privately funded projects and the need to reach a threshold of capabilities to enter the system of public funding.

This paper is structured as follows. After this introduction, section two presents the theoretical framework and key empirical analysis aimed at testing persistence in accessing public funds. The implications of the Matthew effect in the case of high- and low-tech firms are also discussed. In the third section, methodology and data are defined. In the fourth section, the model is estimated and results are discussed. Finally, some conclusions are provided in section five.

2. Literature review and discussion

2.1. Recurrence in accessing public funds: Matthew effect and innovation policy

Innovation literature has long studied the impact of innovation policy on firms' innovative behavior and economic performance. The usual focus is on the crowding-in versus crowding-out impact of public funds on innovation investments and results (e.g.Crespi, D'Este, et al., 2011; Crespi et al., 2014; Ganelli, 2003). Less attention has been paid to the process of allocation of funds and how firms enter and exit the pool of beneficiaries (Antonelli and Crespi, 2013b; Aschhoff, 2009; Radicic et al., 2014). This paper aims at contributing to that gap in the literature by analyzing how past accessing to subsidies for innovation impacts the possibility of accessing in the present.

Literature about persistence in accessing public funds for innovation is based on David's (1994) work related to research funding. He argued that accessing to public funds triggers a reputation effect which positively reinforces a trajectory of gaining grants and subsidies – public and private ones. According to David, this self-reinforcement trajectory improves the productivity of the funded research group and explains the increasing concentration of publications around a stable group of scholars. Although part of the impact is explained by a cumulative advantage effect based on the expected positive feedback between research and resources, there is also a reputation effect, usually referred as Merton's Matthew effect (Merton, 1968). This reputation leads other researchers to focus their attention on the work of 'the elite', which minimizes the time allocated to the search for the most relevant publications. This is also a self-reinforcement mechanism but this time given by the awarding system of science. In this respect, David claims that the Matthew effect leads to a stable equilibrium, where funds are allocated based not necessarily on the quality of the projects but on the number of times researchers are quoted.

The Matthew effect has been applied to the process of public funding of innovation to explain why some firms persist as beneficiaries (Crespi and Antonelli, 2011). There are at least three sources of recurrence that explain this effect. Firstly, to the extent that public offices do not have all the capabilities and information required to optimally select beneficiaries, decisions are based on firm's prior achievements. This way, allocation is based not necessarily on firm's capabilities or the submitted project but on the firm's name and brand. Another incentive to follow this pattern of allocations is that it contributes to a favorable evaluation of the public office since funds are allocated to 'widely known' firms that actually innovate, thus improving office's statistics. Finally, there is a relatively virtuous explanation of the Matthew effect related to the impact of past grants of the firm's ability to submit a project. These firms know the existence of the funding instruments, their characteristics and how to apply. Therefore, they are in a better position to submit a new project than those firms outside the public funding system.

From a theoretical perspective, the impact of the Matthew effect on the efficiency and efficacy of innovation policy cannot be predicted a priori. From a 'picking the winners' perspective, policy should focus on those cases with the maximum probability of success in terms of technological progress, economic impact or a combination of both (see Radicic et al., 2014for a review). Given the fact that a minimum level of capabilities is required to develop, submit and implement an innovation process, and the fact that past innovation processes feedback and enhance capabilities (Aschhoff, 2009; Feldman and Kelly, 2001), one can assume that recurrent firms are in fact the most probable 'winners'. Then, the Matthew effect simplifies the work of public offices to the extent that it allows a quick and clear identification of the best firms (reputation). However, and from a 'spread the seed' perspective (Crespi et al., 2014), technological change can hardly be predicted and public offices lack the information and capabilities to pick the winners in the sense of selecting those projects with the higher probabilities of success. Therefore, recurrence rate should be minimized in order to diversify the population of funded firms. In this case, the Matthew effect accounts for the way public offices deal with imperfect information and works against the efficacy of the policy.

Empirical evidence in this respect is contradictory, although the positive impact of past accessing in present probabilities is verified in all cases. Antonelli and Crespi fund that the Matthew effect is verified for the case of Italian firms, but while it leads to crowding-in effects among high-tech companies, it crowds-out private investments in the case of low-tech ones (Antonelli and Crespi, 2013b; Crespi and Antonelli, 2011). The authors also differentiate between vicious (reputation) and virtuous (accumulation of knowledge) Matthew effects. The former relates to crowding-out impacts on firm's innovation investments and it is present among low-tech Italian firms. The latter is associated to crowing-in effects and it is observed among high-tech companies. Similar results are reached by Gonzalez *et al.* (2005) for the case of Spanish firms: Matthew effect is verified, although with heterogeneous results in terms of crowding-in and -out impacts. Duget (2003), Aschhoff (2009) and Tanayama (2007), in turn, also verifies Matthew effect among subsidized French, German and Finish firms respectively, but it positively impacts firm's investments. Of course, the scarce number of empirical analysis about the allocation of public funds limits the possibility of generalize results. However, empirical approaches seem to confirm the phenomenon although with different levels of intensity which depend on firm's characteristics.

One of the objectives of this paper is to contribute to that gap in the literature by presenting an exploratory exercise to shed light on the existence and magnitude of the Matthew effect and to characterize the subjects of public policy. We claim that part of the persistence rate is explained by the Matthew effect and part by the firm's capabilities. In this respect, another interesting finding of the reviewed studies has to do with the role of capabilities. All of them include variables related to the firm's ability to deal with innovation and find a positive relationship between them and the probability of accessing. Moreover, Aschhoff (2009) and Tanayama (2007) find that investments in innovation are prior to the subsidies. Since investments depend of the firms' ability to plan and implement an innovation project (Nelson, 1991; Teece and Pisano, 1994), evidence seems to confirm the need for a minimum level of capabilities to develop and submit an innovation project to be funded.

Finally, and following the exercise performed by Crespi and Antonelli (2011), we will analyze firms according to their technological intensity. Given the different role of technological capabilities between these firms, and given their differences in terms of size, age, innovative dynamics and productive process, we have good reasons to expect differences in terms of the impact of reputation and capabilities on the probability of accessing public funds for innovations.

2.2. Hypotheses

Figure 1 summarizes the main arguments and hypotheses. H1 refers to the Matthew effect discussed in the literature and observed in other empirical contributions, and a positive relationship between being a beneficiary in the past and being a beneficiary in the present is expected. H1.1. refers to the impact of firm's technological intensity (see appendix A for a detailed sectorial classification). In this case, we do not hypothesize about the sign of the impact, although Crespi and Antonelli's (2011) evidence regarding a vicious Matthew effect (a spurious reputation effect) among low-tech firms leads to expect stronger effects within this group.

H2 is about the role of capabilities and to what extent they are a requisite for accessing public funds in the sense of the evidence reviewed in section 2.1. Given the required abilities to develop, submit and carry on an innovation project, a positive relationship is expected. Although this seems a quite obvious hypothesis, it is not to the extent that its verification would suggest that public funds foster innovation within firms that are actually innovating. Therefore, it would help intensifying innovation processes rather than getting new firms into the innovator's club. Analogously to H1.1, H2.1 refers to the interaction between capabilities and technological intensity. High-tech firms are knowledge intensive enterprises, meaning that capabilities play a key role in the competitive process, therefore, a more intense impact is expected.

Hypotheses can be formulated as follow:

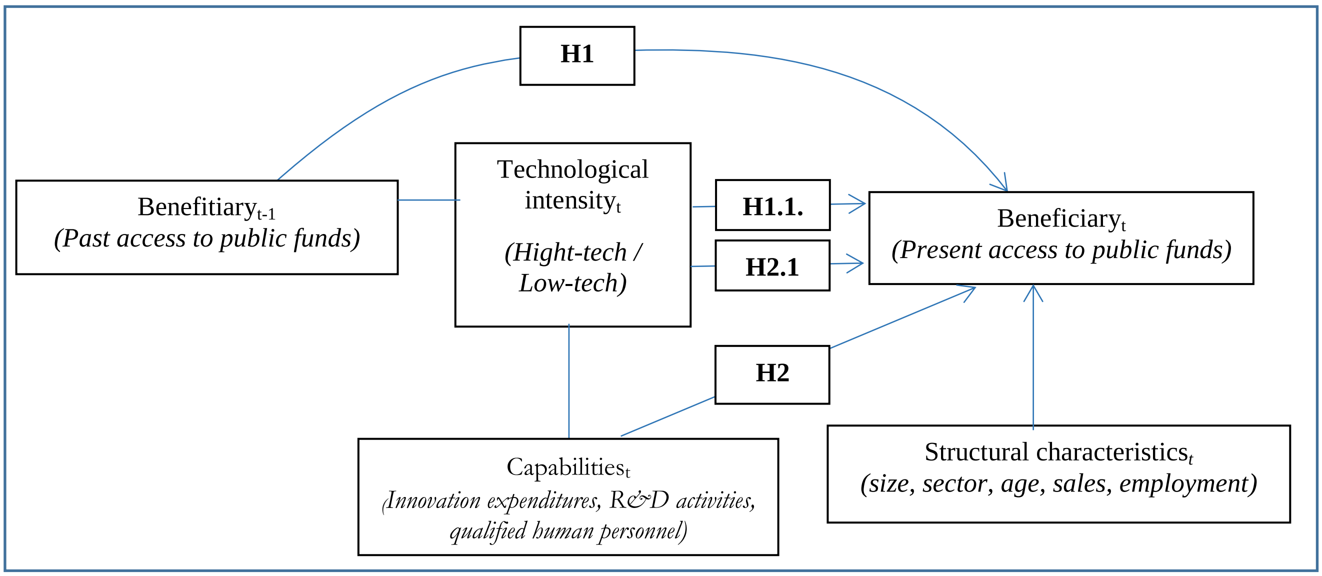
H1: *Past accessing to public funds increases the probability of accessing in the present.*

H.1.1: *The impact of past accessing to public funds differs depending on firm's technological intensity.*

H2: *Firm's capabilities positively impacts the probability of accessing to public funds in the present.*

H 2.1: *The impact of firm's capabilities differs depending on firm's technological intensity.*

Figure 1: Theoretical arguments and hypothesis



3. Model and methodology

3.1. Dataset description

The dataset used in this paper is the result of the integration of the i) register of firms granted with a FONTAR fund - non-refundable grants, subsidize credits and tax refund- during the period 2007-2013; and ii) the innovation surveys these firms answered when they applied to the benefit (hereinafter FONTAR database). The result is a dynamic panel data made of 966 firms and 3337 observations. Besides information regarding the application to FONTAR, the database includes information about innovation and R&D investments, qualified human resources and sector of activity, as well as the traditional economic and structural indicators such as sales, employment, location and age. Unfortunately, data about firms that applied but did not receive a grant is not available. As a consequence, the analysis will account for the population of beneficiaries. However, since FONTAR is the main public instrument to foster innovation with a national scope, our study will account for most of the subsidized firms in Argentina.

It is important to bear in mind that the analysis is performed over a group of firms with higher capabilities than the average of the Argentinean population. Evidence suggest that firms that know about FONTAR are a reduce group, and ever more reduced is the group that actually apply. According to the National Survey of Employment Dynamics and Innovation –an innovation survey similar to the EU-CIS- in 2012, only 35% of Argentinean manufacturer firms knew about the existence of FONTAR and only 8% of the population applied and accessed to a grant (MINCyT, 2015b). As we shall present in section 3.3, the dataset is made of firms with higher capabilities, for instance, to identify funding opportunities, to connect with other agents of the system and to develop an innovation project. In this respect, the dataset has a self-selection bias and although it is representative of the population of firms that accessed the FONTAR, it is not extrapolable to the rest of the Argentinean population. Hence, results have to be read with caution.

3.2. Transition Matrixes

Transition probability matrixes are a very preliminary approach to the persistence in accessing public funds for innovation. This statistical tool allows to model the sequence of subsidized and non-subsidized states as a stochastic process approximated by a two-state Markov chain with transition probabilities. Formally, it can be expressed as follows:

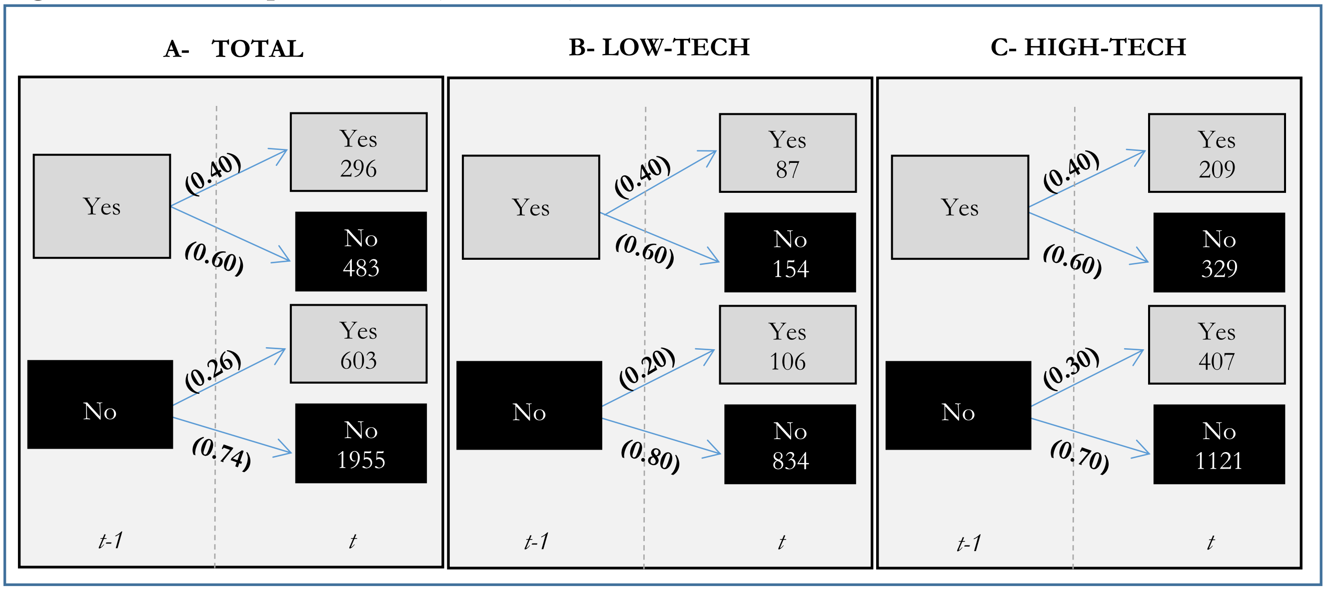
$$P[Y_t = i | Y_{t-1} = j] = \begin{bmatrix} p & (1-p) \\ (1-q) & q \end{bmatrix},$$

where each term of the matrix shows the conditional probability of moving from state *j* to state *i*. Following Roper and Dundas (2008) the analysis of the diagonal term allows the identification of specific patterns of persistence (state dependence). Specifically, persistence is identified if the sum of the main diagonal term is more than one. Additionally, it is possible to identify a state of strong persistence if in a 2-dimensional matrix the sum of the main diagonal terms is more than 1 and–at the same time- all the main diagonal terms are larger than 1/n (in this case 0.5).

Figure 2 illustrates the transition probability matrix for the whole sample, together with information about the number of firms in each group. While the probability of accessing public funding at time t for non-subsidized companies at t-1 is only 0.26, the probability of obtaining subsidies in period t for subsidized firms in period t-1 is 0.40. Symmetrically, the "negative" state dependence appears to be very strong in our sample, with 74% of non-subsidized companies in t-1 still not gaining access to public subsidies at time t. When comparing these results with the literature, a weak positive persistence is observed in the Argentinean case, with a level of state dependence below 0.5. However, a strong negative persistence is verified.

In order to identify sectorial characteristics, firms were classified according to their technological intensity (OECD, 1997). The High-tech group includes high- and medium-high manufacturer and knowledge based service firms. The rest of firms were included in the low-tech group. The rate of positive persistence is similar in both groups. However, the rate of negative persistence is slightly lower among high-tech firms (0.7) and higher among low-tech companies (0.80), with respect to the whole sample. As we shall see, these differences between the high- and the low-tech groups are statistically significant.

Figure 2: Transition probabilities (2007-2013)



Obs. 3337. "Yes (No)" means that the firm has (has not) accessed FONTAR. Inside the boxes: number of firms; inside the brackets: Markov chain probabilities. High Tech includes firms that belong to both high-tech industrial sectors and knowledge base services activities, based on OECD (1997). Low Tech includes the rest. Source: own elaboration based on FONTAR database.

In short, these results provide preliminary evidence about the existence of state dependence in the access to FONTAR. However, neither in the whole sample nor considering high/low technology firms the analysis of the transition probability matrixes indicates a state of strong persistence in the access to innovation support. These results are similar to the ones observed in Crespi and Antonelli (2011) in the sense of the intensity of the persistency rate. In this respect, it is worth to highlight that this analysis do not provide a conclusive evidence of a true state dependence nor the nature of the detected persistence. In the section 3.4 we explore an econometric model that helps to study whether this persistence it is the result of a true or a spurious process.

3.3 *Descriptive statistics*

Table 1 displays the descriptive statistics of innovative indicators stratified according to the taxonomy of persistence in accessing the FONTAR. Total sample is presented in panel A, and the groups of low and high-technology firms are presented in panel B and C, respectively. The complete set of descriptive statistics is presented in appendix b.

Regarding the total sample, two results are worth noting. Firstly, the set of indicators shows figures that are well above the ones that characterize the typical Argentinean firm. For instance, while in the total population of manufacturer firms the proportion of R&D performers reach the 40% (MINCyT, 2015b) while among the firms that accessed FONTAR this indicator ranges from 67% to 84%, depending on the type of persistence (table 1). Similar differences are observed in the case of innovation expenditure and the share of qualified personnel. While the average level of innovation expenditure for the Argentinean manufacturer population is less than US$4100 per employee, this value climbs up to US$ 4900 in average for the whole panel and up to US$ 6650 among firms with positive persistence. Finally, the share of qualified personnel (employees with a university degree) within the panel is on average 32%, which is more than 24 percentage points over the average value for Argentina (MINCyT, 2015b). These differences indicate that firms included in the sample present higher levels of innovation investments than the total population of Argentinean firms. Secondly, the non-parametric correlation test (last row of table 1) reports the presence of a significant relationship between these variables. This means that the state dependence is positively associated with the share of qualified human resources, the share of R&D performers and the innovation intensity.

Finally, the comparison between firms' technological intensity shows that high-tech firms have a more dynamic innovative profile, with higher levels of investments, R&D performing and qualified personnel than low-tech companies. However, within the group of positive persistence, low-tech firms report higher levels of relative innovation investments than the high-tech group. These results could be explained by the type of firm included in this classification. Given that Argentinean structure, the low-tech group includes large and mature firms, with higher levels of financial resources to fund innovations. At the same time, since –by definition- the technological frontier moves slowly within mature sectors, higher levels of investments are required to produce significant innovations. Of course, the right-skewed distribution of innovation intensity could be the reason of this result.

Table 1: Summary Statistics by Taxonomy of persistence

Type of Persistence	**A- Total**			**B- Low Tech**			**C- High Tech**		
	IA intensity	**R&D performers**	**Professionals intensity**	**IA intensity**	**R&D performers**	**Professionals intensity**	**IA intensity**	**R&D performers**	**Professionals intensity**
Positive persistence	6650	0.84	0.34	7941	0.76	0.32	6113	0.88	0.35
	(14,185)	(0.36)	(0.27)	(20,517)	(0.43)	(0.26)	(10,505)	(0.33)	(0.27)
Leaving firms	6521	0.81	0.31	6272	0.78	0.27	6638	0.82	0.34
	(10,480)	(0.39)	(0.26)	(10,713)	(0.42)	(0.25)	(10,384)	(0.38)	(0.27)
New comer firms	5438	0.76	0.33	5989	0.71	0.29	5172	0.78	0.35
	(8,140)	(0.43)	(0.27)	(9,275)	(0.45)	(0.26)	(7,530)	(0.42)	(0.27)
Negative Persistence	4083	0.67	0.32	3694	0.6	0.28	4371	0.72	0.36
	(8,478)	(0.47)	(0.27)	(8,481)	(0.49)	(0.26)	(8,468)	(0.45)	(0.27)
Total	4908	0.72	0.32	4651	0.64	0.27	5066	0.76	0.34
	(9,424)	(0.44)	(0.26)	(10,229)	(0.47)	(0.26)	(8,890)	(0.42)	(0.27)
Kendall tau-b	0.15***	0.14***	0.01	0.17***	0.14***	0.02	0.11***	0.12***	0.02

Note: Figures presented correspond to average values for the period 2007-2013. Standard deviations are reported in brackets. Innovation intensity: ratio between the expenditure on innovative activities and total employment. R&D performers are a binary variable that takes value one when the firm declare a positive expenditure on R&D activities and cero otherwise. Qualified HHRR is the ratio of personnel with a university degree to total employment. *, ** and *** indicate significant levels at 10%, 5% and 1%, respectively. Source: own elaboration based on FONTAR database.

3.4 Econometric model: Empirical Strategy and Explanatory Variables

To model benefit dynamics, an approach based on models of annual probabilities of entering to and exiting from receipt (also known as transition probability models) was used. This approach helps to explore the determinants of firm-level persistence in gaining public support by means of a probit model in which the dependent variable is affected by a set of exogenous control variables ($X_{i,t}$) and by the lagged specification of the dependent variable ($y_{i,t-1}$):

$$\mathrm{P}\left(y_{i,t} = 1 \middle| X_{i,t}, y_{i,t-1}\right) = \lambda y_{i,t-1} + X'_{i,t}\beta + \alpha_i + u_{i,t} \quad (1)$$

The presence of the lagged outcome variable allows testing the hypothesis of true state dependence. The larger the value of λ, the greater the degree of state dependence in benefit receipt probabilities. Unobserved firm heterogeneity is characterised by a fixed specific component (α_i) and a white noise error component ($u_{i,t}$). This last error term is uncorrelated to both the fixed-in-time component and the set of explanatory variables includes in $X_{i,t}$. To allow for correlation between α_i and $X_{i,t}$ we follow the proposition of Mundlak (1978) and Chamberlain (1984):

$$\alpha_i = \xi' \bar{Z}_i + u_i \quad (2)$$

where u_i is assumed independent of $X_{i,t}$ and $u_{i,t}$ for all the firms and time periods. $\bar{Z}_i$ may be defined in several ways, we follow the common practice of defining it as the longitudinal average of firm structural characteristics. The assumption is that differences in longitudinal averaged characteristics are informative about the underlying firm-specific characteristics, so that the individual differences that are left (*ui*) may be more plausibly supposed to be independent of observed characteristics ($X'_{i,t}$ and $y_{i,t-1}$).

Finally, there is the estimation of the initial condition of the sequence of observations for each firm. If being beneficiary in the initial year $y_{i,1}$ is correlated with the time-invariant individual-specific effect u_i, a correlation is induced between the error term and the lagged dependent variable, leading to bias in parameter estimates. To avoid this problem, we employ the conditional maximum likelihood estimator proposed by Wooldridge (2005) that consist of modelling the distribution of the binary receipt from $t = 2,3, \dots, T_i$ and conditioning on a set of explanatory variables and the binary receipt indicator for the initial year. According to that, the dynamic equation becomes:

$$\mathrm{P}\left(y_{i,t} = 1 \middle| X_{i,t}, y_{i,t-1}\right) = \lambda y_{i,t-1} + \beta' X_{i,t} + \alpha_0 + \alpha_1 y_{i,1} + \xi' \bar{Z}_i + u_i + u_{i,t} \quad t = 2, \dots, T_i \quad (3)$$

Summing up, the set of explanatory variables can be categorized in three groups. Firstly, there are individual-level variables which summarize firms' characteristics: high tech, age, size, innovation intensity, qualified human resources and R&D expenditure. Secondly, there are longitudinal-averaged variables which correspond to the firm' structural characteristics which were used to implement the Mundlak-Chamberlain approach: employment and market performance. Thirdly there are variables that take into account variations in receipt probabilities associated to both calendar time and regional characteristics, that are not captured by other variables: region and year. Table 2 presents a detailed description of the explanatory variables used in the baseline model.

Table 2: Summary of the main variables

Variable	Description	Values
Firms Characteristics		
High Tech	Classification of manufacturing industries based on R&D intensities, and of services industries based on intensity of knowledge.	1 if firms belong to Medium or Medium High technology industry or a Knowledge Intensive Business Services; 0 otherwise
Age	Firms' age based on years since foundation.	1 to ∞
Size	Firms' total employment	1: micro / 2: small / 3: medium / 4: large
Innovation intensity	Ratio of Innovation Expenditures to firms' total employment.	0 to 1
Qualified human resources	Ratio of personnel with a university degree to total employment.	0 to 1
R&D Expenditure	R&D expenditure	1 if the R&D expenditure is greater than zero; 0 otherwise
Longitudinal-averaged firm' structural characteristics		
Employment	Average of firms' total employment	0 to ∞
Market Performance	Average of firms' total sales	0 to ∞
Time and Regional Fixed Effects		
Region	Set of binary variables that indicates geographical location of firms.	1: north-west / 2: north-east / 3: center / 4: south
Year	Set of binay variables that indicates time-fixed effects.	2007-2013, 6 dummies
Adjudication Variables		
FONTAR t-1	Lag of innovation subsidy in t	1 if firms receipt an innovation support in t; 0 otherwise
FONTAR t=1	Innovation subsidy at the initial period	1 if firms receipt an innovation support in initial period; 0 otherwise

4. Results: model estimates and interpretation

Two main groups of estimates are presented in this section. Table 3 is based on equation (1) and reports estimates using three different models to check the robustness of results: i) a pooled probit model, ii) a dynamic random effects probit model assuming that initial conditions are exogenous, and finally iii) a model that assumes endogenous initial conditions. Table 4 is based on the equation (3) and presents estimates in which the basic model is augmented with interaction effects that allow the degree of state dependence (and the rest of explanatory variables) to vary between high- and low-tech firms. It is worth to mention that in both groups the estimation of marginal effects is reported.

Regarding table 3, explanatory variables are defined so that the reference categories characterize the situation of a low-tech micro firm. The first row of the table shows the estimate of λ, the degree of state dependence. Looking at table 4 as a whole, state dependence in public support in all the models is positive and statistically significant. This verifies the robustness of the empirical strategy. Results show that past access to FONTAR increases the probability of accessing in the present, thus confirming the presence of Matthew effects and H1.

In terms of the marginal effect, the estimates for the lagged dependent variable lies in the range between 0.096 and 0.061 showing the overestimation of the probit model and the dynamic model that assumes exogenous initial conditions. According to the results present in the third column, on average -and controlling for firm's heterogeneity- past accessing to public funds is associated with a difference of almost 6 percentage points in accessing in the present. Additionally, firm's innovative capabilities and qualified human resources also explain the probability of accessing. This result provides evidence regarding the presence of a 'capability effect', thus confirming H2.

Table 3: Dynamic effects probit

	(1)	(2)	(3)
		Dynamic Random Effect Probit	
	Pooled Probit	**Exogenous Initial Conditions**	**Endogenous Initial Conditions**
Received FONTAR at t-1	0.096**	0.064**	0.061**
	(0.017)	(0.023)	(0.023)
=1 if firms spend on R&D activities	0.057**	0.057**	0.057**
	(0.018)	(0.019)	(0.019)
Ratio Innovative Activities / Total Employment	0.000*	0.000**	0.000*
	(0.000)	(0.000)	(0.000)
Ratio Professionals / Total Employment	0.060+	0.059+	0.056+
	(0.031)	(0.033)	(0.034)
Size - Small	0.033+	0.033	0.030
	(0.020)	(0.021)	(0.021)
Size - Medium	0.111**	0.113**	0.103**
	(0.025)	(0.027)	(0.035)
Size - Big	0.172**	0.179**	0.142
	(0.047)	(0.051)	(0.094)
Age	-0.000	-0.000	-0.000
	(0.001)	(0.001)	(0.001)
=1 if High-Technology Industry or Knowledge-Intensive Business Service		0.063**	0.062**
		(0.017)	(0.017)
Received FONTAR at t=1			0.050
			(0.044)
Sigma-u		0.287	0.288
Rho		0.0760	0.0765
Observations	3,337	3,337	3,337
No. Firms		966	966
Year FE	YES	YES	YES
Regional FE	YES	YES	YES
Time-averaged characteristics	NO	NO	YES

Note: Estimated results corresponds to Marginal Effects. Robust standard errors are reported between brackets. Base category: Micro Firms of Low-technology Industries and Non-Knowledge Intensive Business Services. Significance Levels: ** p<0.01, * p<0.05, + p<0.1. Source: own elaboration based on FONTAR database.

Table 4 displays the estimated results when firms are analyzed in terms of their technological intensity. The estimate of λ (i.e., the presence of Matthew effect) is stronger among low-tech firms. For example, for a low-tech firm past accesses to FONTAR (state dependence) increases the probability of receiving a public support in 7.5 percentage points while for a high-tech firm the marginal effect shows a positive impact of 4.8 percentage points. Conversely, the share of qualified personnel –a traditional proxy of capabilities- shows the highest impact among high-tech companies. Similar to the findings reviewed for other countries, innovation variables are significant. The performance of R&D has the highest impact on the dependent variable in the case of high-tech firms and an impact similar to the Matthew effect among low-tech ones. These results suggest that although Matthew effect is present and differs between high- and low-tech firms, capabilities also play a key role especially among the former ones.

Table 4: Dynamic effects probit models of the probability of receipt at year t interview

	(1) Total	**(2) Low Tech**	**(3) High Tech**
Received FONTAR at t-1	0.061**	0.075*	0.048+
	(0.023)	(0.037)	(0.029)
=1 if spend on R&D activities	0.057**	0.071**	0.051+
	(0.019)	(0.027)	(0.026)
Ratio Innovative Activities / Total Employment	0.000*	0.000*	0.000
	(0.000)	(0.000)	(0.000)
Ratio Professionals / Total Employment	0.056+	0.064	0.080+
	(0.034)	(0.058)	(0.048)
Size - Small	0.030	-0.014	0.070*
	(0.021)	(0.036)	(0.031)
Size - Medium	0.103**	0.071	0.135**
	(0.035)	(0.052)	(0.047)
Size - Big	0.142	0.197	0.117
	(0.094)	(0.125)	(0.113)
Age	-0.000	-0.001	0.001
	(0.001)	(0.001)	(0.001)
=1 if High-Tech	0.062**		
	(0.017)		
=1 if Industry Sector		0.095+	
		(0.054)	
=1 if Service Sector		0.117*	-0.020
		(0.055)	(0.028)
Received FONTAR at t=1	0.050	0.028	0.085
	(0.044)	(0.093)	(0.052)
Sigma-u	0.288	0.309	0.259
Rho	0.0765	0.0869	0.0628
Observations	3,337	1,195	2,066
No. Firms	966	355	583
Year FE	YES	YES	YES
Regional FE	YES	YES	YES
Time-averaged characteristics	YES	YES	YES

Note: Estimated results corresponds to Marginal Effects. Robust standard errors are reported between. Base Category: Micro Firms of Low-technology Industries and Non-Knowledge Intensive Business Services. Significance Levels: ** p<0.01, * p<0.05, + p<0.1. Source: own elaboration based on FONTAR database.

4. Conclusion

The objective of this paper was to analyze the process of allocation of public funds for innovation, in order to test the presence of Matthew effects. The hypotheses stated that past access to public funds for innovation increases the probabilities of accessing in the present. The dataset was made of 966 firms that accessed the FONTAR during 2007-2013 –around 3300 observations. Methodologically speaking, the approach consisted of testing the existence of state dependence and a series of dynamic random effects probit models were estimated, where unobservable characteristics and initial conditions were controlled. Results confirm the hypotheses and the existence of Matthew effects: past access to FONTAR increases in 6 percentage points the probability of accessing in the present. They also show that firm's qualified human resources explain the probability of accessing in 5.6 percentage points, which provides evidence regarding the presence of a 'capability effect'. When firms are analyzed in terms of technological intensity, the Matthew effect is stronger among low-tech firms (7.5 percentage points), while the share of qualified personnel –a traditional proxy of capabilities- has the highest impact among high-tech companies (8 percentage points).

Results are in line with the literature: past accessing to public support positively impact on the probability of accessing in the present (Antonelli and Crespi, 2013b; Aschhoff, 2009; Crespi and Antonelli, 2011; Duguet, 2003; González et al., 2005; Radicic et al., 2014; Tanayama, 2007). Evidence suggests that once the firm entered the system, it remains with an active innovative behavior, not just because of the reputation effect or how easily they prepare and submit a project, but also because it has accumulated capabilities and sunk investments in the pursuit of a technological competitive advantage. Results also agree with the persistence literature regarding the existence of heterogeneity. Although it is not strictly comparable, our findings are similar to those of Crespi and Antonelli (2011) regarding differences in the Matthew effect whether the firms is a high- or a low-tech company. Findings are also similar to those presented by Aschhoff (2009) in the sense that firm's innovation investments and capabilities positively impact on the probability of getting granted. Results also agree with the literature that sustains that past innovation processes positively feedback on present capabilities and, consequently, the probability of initiate a new innovation process (Antonelli, 1997; Malerba et al., 1997; Roper and Hewitt-Dundas, 2008, among others).

In short, there seems to be a virtuous circle where funded firms develop innovation processes that feedback their capabilities and their possibility of funding new innovation processes. This funding results from higher incomes from past innovation processes but also from the accessing to public support for innovation, which increases the probability of actually innovate and reduces the cost of innovating. Of course, the existence of negative persistence poses questions regarding the possibility of a vicious circle where firms cannot access to public support because of their low capabilities, and they cannot increase their capabilities because of lack of funding for innovation. Future research could shed light on both circles and related to that, it is worth to mention some limitations of this research.

The main limitation has to do with the dataset. Since the panel is made of firms and accessed at least once to the FONTAR, there is a bias towards firms with higher capabilities than the average of the population, which impacts –among other things- on the characteristics of the innovative process these firms carry on. Another limitation of this study –and problem also within the literature- is the time elapse between receiving a grand and applying and receiving the next one. More complex projects might take longer periods wile simple innovation activities might take shorter ones. Therefore, persistence is only partially captured. Since this study is part of a larger research project, we hope future analyses and the merging of the dataset with innovation and industrial surveys will help to overcome part of these limitations. However, the research presented here confirms the existence of Matthew effects, which also differs depending on the firm's technological intensity. It also confirms the impact of capabilities on accessing public support for innovation and, what is more important, the role played by public funds in triggering a sustained innovative behavior on granted firms.

Appendix

A – Sectorial classification – Technological intensity

Classification	Sectors (CIIU rev. 3.1.)
High-tech	Manufacturer industry: 2423, 30, 32, 33, 3530, 34, 24, 29, 31, 3520, 3590.
	Service sector: 6521, 7210, 7300, 7410, 7421, 7422, 7430, 7499, 9211, 7220, 7290
Low-tech	Manufacturer industry: rest of manufacturer industries.
	Service sector: rest of service industries.

Source: own elaboration based on OECD (1997) and (OECD, 2012).

B- Descriptive statistics

	R&D Performers		Innovation Intensity		Qualified human resources		Age		Turnover	
	Mean	**Sd**	**Mean**	**Sd**	**Mean**	**Sd**	**Mean**	**Sd**	**Mean**	**Sd**
Size										
Micro	0.60	(0.50)	7,408	(14,270)	0.50	(0.30)	13	(9)	688	(5,466)
Small	0.70	(0.40)	4,787	(7,950)	0.30	(0.20)	18	(11)	1,969	(2,324)
Medium	0.70	(0.40)	3,028	(4,118)	0.20	(0.20)	26	(16)	8,217	(7,555)
Big	0.88	(0.10)	2,610	(3,075)	0.20	(0.20)	25	(15)	12,591	(20,124)
High-Technology Industry or Knowledge-Intensive Service										
Low-Tech	0.90	(0.30)	4,663	(9,979)	0.30	(0.30)	25	(16)	3,898	(7,094)
High-Tech	0.90	(0.20)	4,972	(8,615)	0.30	(0.30)	23	(14)	4,152	(9,204)
Year										
2007	0.90	(0.30)	3,992	(8,423)	0.30	(0.30)	22	(14)	2,497	(3,887)
2008	0.80	(0.40)	4,565	(8,227)	0.30	(0.30)	21	(14)	3,249	(5,079)
2009	0.70	(0.40)	4,216	(6,231)	0.30	(0.30)	20	(14)	3,070	(7,081)

2010	0.70	(0.40)	4,601	(9,283)	0.30	(0.30)	20	(14)	3,768	(7,797)
2011	0.80	(0.40)	5,671	(12,337)	0.30	(0.30)	19	(14)	5,008	(11,763)
2012	0.90	(0.30)	5,886	(8,787)	0.30	(0.30)	19	(14)	5,538	(8,395)
2013	1.00	(0.20)	5,248	(7,175)	0.30	(0.30)	18	(14)	7,577	(11,831)
Total	**0.70**	**(0.40)**	**4,908**	**(9,424)**	**0.30**	**(0.30)**	**20**	**(14)**	**4,075**	**(6,687)**

Note: Average values for the period 2007-2013. Standard deviations are reported between brackets. Innovation intensity is the ratio between the expenditure on innovative activities and total employment, R&D performers is a binary variable that takes value one when the firm declare a positive expenditure on R&D activities, and Qualified HHRR is the ratio of personnel with a university degree to total employment, Age indicates the number of years since the start of the firm, and Turnover reports the firms' sales in thousands dollars. *, ** and *** indicate significant levels at 10%, 5% and 1%, respectively. Source: own elaboration based on FONTAR database.

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