MATTHEW EFFECTS AND R&D SUBSIDIES: KNOWLEDGE CUMULABILITY IN HIGH-TECH AND LOW-TECH INDUSTRIES[1]

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Abstract

The paper explores the causes and effects of persistence in the discretionary allocation of public subsidies to R&D activities performed by private firms in high-tech and low-tech industries. It applies the crucial distinction between past dependent reputation-Matthew-effects and path dependent competence-Matthew-effects. The former qualifies the persistence in the discretionary allocation of public subsidies in terms of sheer information externalities exclusively based upon previous awards. The latter is identified by the role of the accumulation of competence stemming from past grants in current R&D activities. The paper articulates and tests the hypothesis that knowledge cumulability matters in assessing whether vicious or virtuous Matthew effects prevail. Competence-Matthew-effects are identified by the actual increase of total R&D activities of the recipients of public grants in the past. Virtuous Matthew effects are found in high-tech industries where learning, learning to learn and knowledge cumulability are higher. In traditional industries, vicious Matthew effects prevail for the lower levels of knowledge cumulability. Here reputation-Matthew-effects can lead to substitution of private funds with public ones. A rich and detailed empirical analysis including Transition Probability Matrices, probit regression and Propensity Score Matching on a database of around 700 Italian firms in the years 1998-2003, confirms the hypothesis and suggests that the selective use of discretionary allocation should be applied in high tech industries. The identification and appreciation of the key role of knowledge cumulability can become a major target for an effective innovation policy

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1. Introduction

In the last decade there has been a rise in the perceived relevance of technology policy in promoting productivity and economic growth and large amounts of public funds have been spent on programs to stimulate the generation of new scientific knowledge in research institutions and to support innovative activities performed by private firms (OECD, 2007 and 2010). Indeed, the fostering of R&D investment is a major issue for long-term European policy strategy (European Commission, 2002 and 2010; Archibugi and Filippetti, 2011).

However, it has been recognised that relevant government failures may take place in this field of policy intervention (Niman, 1995) and that consequently there is considerable scope to improve the efficiency of government spending (Conte et al., 2009). In this paper we will focus on a specific but crucial issue i.e. the choice on the targeting of policy intervention given the existence of structural differences across sectors of economic activity (Jang and Huang, 2005; Crespi and Pianta, 2008). As suggested by Ortega Gilles et al. (2010) the relationship between R&D and productivity is not homogeneous across different industries. On the contrary, as they showed, R&D investment in high-tech sectors are more productive than in low-tech sectors: This evidence supports the view that industrial and innovation policies should be targeted at increasing R&D in high-tech sectors and at supporting overall capital formation in low-tech sectors.

In this paper we will argue that not only fostering R&D in high-tech sectors might be more productive but that the effectiveness of a traditional major tool of innovation policy i.e R&D subsidies might be greater in high-tech sectors than in low-tech industries. This argument is theoretically grounded on the critique alleged by the literature to discretionary support to R&D activities because of the possible bias in favour of past recipients, with the creation of clubbish procedures of allocation based upon reputation effects that are not substantiated by actual research capabilities. In particular, the paper applies to research policy the notion of Matthew effects drawn from the economics of science and implements the distinction between *virtuous* and *vicious* Matthew effects. The former consist in the persistence of the physiological provision of subsidies to firms that have been actually able to use previous subsidies to effectively increase, in subsequent times, their R&D activities and innovation capabilities. The latter include the cases of pathological persistence in the assignment of public subsidies based on sheer reputation, even to firms that have actually reduced their commitment to research after receiving previous subsidies (David, 1994). We argue that the characters of the knowledge generation process play a key role in discriminating among virtuous and vicious Matthew effects. The levels of knowledge cumulability, R&D sunk costs and learning to learn have a direct bearing upon the likelihood that the prior allocation of public subsidies exerts a positive effect upon the actual capability of the recipients to undertake successful research processes. Since industrial sectors widely differ in terms of these aspects, we claim that sectoral patterns in the nature of Matthew effects can be identified and that while the allocation of public subsidies in high-tech sectors is likely to activate virtuous Matthew effects, when firms produce in traditional industries selection committees are more likely to be biased by sheer reputation effects.

The relevance of these arguments is empirically tested by implementing a framework of analysis based on transition probabilities matrixes, an econometric model of the determinants of firm's access to R&D grants and an evaluation impact analysis applying the Propensity Score Matching method. The empirical analysis is based on the rich information contained in two waves of the Survey on Italian Manufacturing Firms realised by the Unicredit Group. Each wave collects contemporary and retrospective (previous three years) data from samples of more than four thousand firms. In order to obtain a dataset for the study, with two distinct points of observation, it has been necessary to merge the two waves (covering the years from 1998 to 2003). The matched database, containing data for the years 1998-2003, covers around 750 manufacturing firms observed in both the two periods.

The remainder of the paper is as follows. Section 2 provides the theoretical background for our analysis and discusses our hypotheses. Section 3 presents the empirical strategy of the study and the descriptive analysis, while sections 4 and 5 discuss respectively methodology and results of the econometric analysis. Conclusions and policy implications are in Section 6.

2. The Matthew effect in discretionary R&D subsidies

A critical issue in the discretionary allocation of R&D subsidies is related to the substantial persistence observed in the outcome of selection procedures. Such a persistence is usually meant to be dysfunctional since it suggests that committees that should identify the actual quality of the research projects are biased by the reputation of the firms performing them. The members of the selection committees would be too much influenced by the scientific and technological reputation of the candidates, rather than by the sheer quality of the projects. Actually the reputation of the candidates would become a reliable proxy for the quality of the projects. Such reputation would be strongly influenced by previous awards and specifically by the inclusion in precedent assignment tournaments. The claim is that firms that have already received a selective subsidy based upon discretionary procedures censed to screen their quality of the projects in the past have disproportionately higher chances to be selected again, simply because of their acquired reputation, and not because of a correct assessment of their actual efforts. According to these criticisms a vicious 'Matthew effect', i.e. a dysfunctional persistence, would take place in the selective allocation of public subsidies based upon beauty contexts. Their claim, in other words, is the evident persistence in the allocation of public subsidies by means of beauty context procedures is necessarily perverse, as it cannot reflect other dynamic effects that are not based upon reputation so as to lead to the inclusion of *phoney* innovators and the exclusion of '*hungry orphans*' with high levels of research capabilities (See Table 1).

However, when knowledge cumulability matters and the allocation of subsidies in the past helps increasing the current competence of past recipients, the persistence in the allocation of public subsidies by means of discretionary procedures is not necessarily product of dysfunctional reputation effects. On the contrary, the observed persistence can be the result of positive effects of past public subsidies on the current performances of firms in innovation activities. This argument builds upon the analysis of the knowledge generation process and the appreciation of the actual levels of knowledge cumulability. Knowledge generation is characterized by learning processes, high levels of sunk costs and hence economies of density and cumulability. New knowledge impinges upon the competence acquired by means of learning processes and is the result of the recombination of existing bits of knowledge. For a given amount of resources invested in R&D, the larger is the stock of knowledge of each firm and the larger the chances to generate new technological knowledge. Consequently the larger is the actual cumulability of knowledge and the stronger are the levels of competence, the higher the quality of research projects and hence the incentive for the recipients of public subsidies at time t-1 to perform and fund privately R&D activities at time t (Arrow, 1962a, 1962b, 1969; Stiglitz, 1987; Romer, 1990; Weitzman, 1996).

When knowledge cumulability is relevant, the persistence in the allocation of subsidies would simply reflect the higher levels of current commitment of past recipients in R&D activities. The intrinsic non-ergodic, persistent character of discretionary allocation processes is 'virtuous': there is no room for the allegation of an economic dysfunctionality. Committees members are perfectly right in confirming their preferences for firms that have taken advantage of previous awards simply because their projects reflect a larger amount of inputs, higher levels of competence and expertise and hence are simply of a higher and better quality. In this case the selection procedure is effectively able to sort out phoney innovators and to include, repeatedly, competent firms. When knowledge cumulability matters virtuous 'Matthew effects' are more likely to take place (Antonelli and Crespi, 2011)[2].

The distinction between vicious and virtuous Matthew effects is most important with respect to the characteristics of the dynamics at work (see Table 1). Matthew dynamics is clearly non-ergodic as past events have an effect through time. When vicious Matthew effects apply, however, the dynamics of the process is past dependent. Once a firm has received a subsidy, the snow-ball effect of cumulative and self-reinforcing reputational effects will keep going, whatever the firm does along the process. When, instead, competence, virtuous Matthew effects apply, committee members should be able to value firms' actual technological competence possibly enriched by previous grants allocation. In this case the process is path

[2] As it is often the case in the recombinant generation of new knowledge, the application of a concept elaborated in a field to another one yields new and unexpected results as it provides new opportunities for investigation. The use of the notion of Matthew effects originally introduced in the sociology of science and elaborated in the economics of science to the economics of R&D is especially fertile for the larger availability of direct and qualified measures of the actual efforts and competence of researchers, that are often lacking in scientometrics (Arora and Gambardella, 1997; Arora et al., 1998).

dependent: the initial conditions – i.e. the allocation of a public subsidy at time t-1- does not guarantee that the firm will receive a subsidy in the future. In the virtuous Matthew effect the past allocation increases the final outcome of the selection process if and when it actually increased the knowledge base and the competence of the firm, hence the profitability of current R&D. The virtuous Matthew effects may take place when knowledge cumulability stirred by past allocations exerts positive effects on learning to learn and economies of density in performing research activities characterized by sunk costs, but it is far from being automatic: the conduct of agents along the process matters in the actual definition of the levels of total R&D expenditures (David, Hall, Toole, 2000).

[Table 1, about here]

It becomes clear that, for given levels of competence and integrity of the selection committees, the actual levels of knowledge cumulability, knowledge economies of density and the actual rates of the dynamics of learning to learn play a major role in shaping the likelihood that either virtuous or vicious Matthew effects. Such levels vary a lot across industries and firms (Antonelli, Crespi, Scellato, 2010a and b).

In the high-tech science based industries the generation of technological knowledge is characterized by high levels of cumulativity with actual persistence in the introduction of innovations at the firm level (Ortega-Argiles et al., 2010; Antonelli et al., 2010). In these industries the experts of the selection committees have much more opportunities to assess the actual quality of the research projects: the proximity to scientific knowledge helps the screening process and favours the inclusion of high quality projects and the exclusion of phoney innovators. The allocation of public subsidies in prior discretionary rounds is likely to positively affect the actual enlargement of the knowledge base of the firm, to increase its opportunity to learn to learn and to take advantage of economies of density stemming from the sunk costs (Lee, 2011). Hence following Merton we can believe that prior subsidies have actually been instrumental "for enlarging their role as investigators" (Merton, 1968:57). In sum, the allocation of public subsidies by means of discretionary procedures in high-tech sectors is likely to activate virtuous Matthew effects (Gonzalez et al. , 2005 and 2008) and to complement internal funds for R&D activities (García-Quevedo, 2004).

On the opposite, in traditional sectors where the cumulativity of technological knowledge is much lower, process innovations purchased from upstream suppliers prevail and the introduction of product innovation is occasional, there is a stronger possibility that the allocation of public subsidies based on discretionary procedures is more influenced by reputation effects (Almus, Czarnitzki, 2003; Busom, 2000). The members of the selection committees can rely less of the scientific content of the project to assess their quality. The reputation based upon previous inclusions may have stronger effects, because of higher levels of subjectivity in the assessment. The probabilities of inclusion of phoney innovators and unfair exclusion of true innovators –hungry orphans- are higher. The allocation of previous subsidies may

have engendered typical crowding out effects with the substitution of private funds with public ones and hence no increase in the actual levels of research intensity (Kauko, 1996; Klette et al., 2000).
The observation of the actual outcome of the delivery of past allocations with respect to their additionality and effectiveness helps discriminating between the two types of Matthew effects. As far as the additionality is concerned it is important to assess whether the provision of public subsidies has led to the substitution of private funds. Virtuous Matthew effects are expected to be dominant where subsidies produce an increase of total R&D budgets and flows of innovation being introduced. Instead, vicious, reputation Matthew effects are prevalent where substitution of private funds with public subsidies is detected.
Summing up, building on previous arguments our set of hypotheses can be synthesized as it follows:

H1: Matthew effects are at work with non-ergodic dynamics. We expect that significant persistence takes place in the allocation of public subsidies.
H2: Competence, virtuous Matthew effects matter with path dependent dynamics in high-tech industries where knowledge cumulativity is higher and key characteristics the firms including research efforts can be considered as reliable clues reflecting the true levels of technological competence. Hence, we expect that in high-tech industries subsidies produce additionality effects in R&D efforts.
H3: Reputation, vicious Matthew Effects are expected to apply to low-tech industries with past dependent dynamics. Reputation Matthew effects take place when selection committees, unable to assess the true content of the research proposal, because of its low scientific content, are mainly influenced by the information on previous subsidies' allocation. Therefore, in this context the risk of crowding out effects associated with subsidies is higher.

3. Empirical strategy and descriptive analysis

In our empirical analysis we follow three different but complementary approaches. The first aims at the identification of firm-level persistence in the access to R&D subsidies by means of Transition Probability Matrixes (TPM). The second explores the determinants of firm-level persistence in gaining public support by means of a probit model. Finally, the third applies a propensity score matching method to evaluate the impact of public subsidies on firms' innovative investments.
The analysis is based on a dataset derived from the questionnaire surveys developed originally by the investment bank Mediocredito Centrale (MCC, now Unicredit), regarding a representative sample of Italian manufacturing firms with more than 11 employees. The original MCC database comes from two different questionnaire waves, each of them collecting contemporary and retrospective (previous three years) data from samples of more than 4000 firms. In order to obtain a dataset for our study, we merged two waves (covering years from 1998 to 2003). We finally

cleaned the dataset by eliminating outliers, ending up with a balanced dataset of 752 manufacturing firms observed twice over a 6-year period[3].

Table 2 provides some descriptive statistics of the sample with respect to key variables for our analysis. The percentage of firms who have accessed to R&D subsidies (either of national or EU source) were respectively 13.56% in the period 1998-2000 and 22.61% in the period 2001-2003. In this last period in high-tech sectors 26.8% of firms was subsidized while in low-tech sectors the percentage was 18.8%[4]. Table 2 shows the presence of significant differences in the values of key variables including R&D investments between subsidized and non-subsidized companies. Such differences cannot be attributed to the work of R&D subsidies since they may simply reflect the selective nature of the group of funded firms. As it will be further discussed, this issue should be taken into account in the evaluation impact analysis.

[Insert Table 2 here]

The analysis of firm-level persistence in the access to R&D subsidies starts with the exam of the evidence provided by transition probability matrixes. 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:

$$P[X_t = i \mid X_{t-1} = j] = \begin{bmatrix} p,(1-p) \\ (1-q),q \end{bmatrix}$$

Each term of the (2X2) TPM will be the conditional probability $p_{ij} = P(I_t = j \mid I_{t-1} = i)$, or the probability of moving from state j to state i.

The analysis of the diagonal terms, based on estimated transition probabilities (Roper and Dundas, 2008), allows the identification of specific patterns of persistence (Table 3 and Table 4). In the case of a 2-dimensional matrix there is evidence of persistence if the sum of the main diagonal terms is more than 1. Strong persistence is identified if the sum of the main diagonal terms is more than 1 and all the main diagonal terms are larger than 1/n (in this case 0.5).

[Insert Table 3 here]

The study of the whole sample shows that while the probability of accessing public funding at time t for non-subsidized companies at t-1 is only 0.19, the probability of obtaining R&D subsidies in period t for subsidized firms in period t-1 is 0.45: more

3 A more detailed description of the database is provided in Antonelli and Crespi (2011).

4 Sectors have been classified according to the OECD classification. In the group of high-tech sectors we included medium-high technology industries; in the group of low-tech sectors we included medium-low technology industries.

than the double. Symmetrically, the "negative" state dependence appears to be very strong in our sample, with 81% of non-subsidized companies in t-1 still not gaining access to public subsidies at time t.

The distinction between the sectoral composition of the sample in terms of different technological intensity of industries is also telling (Table 4). In the case of low-tech sectors the sum of the main diagonal terms is more than 1, with both the elements greater than 0.5 indicating the presence of strong persistence. In particular, for companies operating in this class of industries, while the probability of accessing public funding at time t for non-subsidized companies at t-1 is 0.16, the probability of obtaining R&D subsidies in period t for subsidized firms in period t-1 is 0.50 (more than three times). In the same way the "negative" state dependence is strong with the share of non-subsidized companies in t-1 still not gaining access to public subsidies at time t equal to 0.84.

Companies belonging to high-tech sectors are also characterised by persistence in the access to public subsidies, since the sum of the main diagonal terms is more than 1. However, our data show a lower level of state dependence with respect to the former case. The probability of accessing public funding at time t for non-subsidized companies at t-1 is 0.23, while the probability of obtaining R&D subsidies in period t for subsidized firms in period t-1 is 0.42 (nearly the double).

[Insert Table 4 here]

Such results provide preliminary indications for state dependence in firm's access to public funds for R&D investments, with differentiated patterns of persistence across groups of sectors classified by their technological intensity. However, they do not provide, yet, a satisfactory and conclusive evidence that the observed persistence can be identified as true state persistence. Moreover, nothing can be said –yet- on the nature of the detected persistence, whether it is the result of a virtuous or a vicious process. The econometric analysis proposed in the next section aims specifically at isolating true state persistence effects, by controlling for a number of observable characteristics of firms that might shape the patterns of subsidies' allocation and influence the identified persistence. Moreover, the probit models and the impact evaluation exercise will help us to qualify the nature of the observed persistence effects and its differentiated impact across groups of firms operating in sectors characterized by a different technology intensity.

4. Econometric analysis

In this section we present the econometric model that tests the determinants of the access to R&D public support with special attention to firm's past subsidy history and the methodology applied for the impact evaluation exercise. The analysis is based on a probit model in which the dependent variable is affected by a set of exogenous control variables and by the lagged specification of the dependent variable. The presence of the lagged outcome variable allows us to test the

hypothesis of true state dependence. In this way we aim at capturing the effect on firms' current subsidy status of the event of being subsidized or not at time t-1.
In our econometric analysis we estimate a probit model of the event (Y=1) of receiving a public R&D subsidy that can be represented as follows:

$$Pr(Y_{it} = 1 \mid X_{it-1}, Y_{it-1}) \qquad (1)$$

where $X_{i,t-1}$ is a vector of observable firm i's characteristics at t-1 and Y_{it-1} the event of being subsidized or not at time t-1[5].

Control variables beside firms' past R&D subsidy history have been selected in this study according to the empirical evidence that analysed this probability (Busom, 2000; Wallsten, 2000; Arvanitis et al., 2002; Almus and Czarnitzki, 2003; Duguet, 2004; Blanes and Busom, 2004; Görg, H. and E. Strobl, 2007; Hussinger, 2008). The theoretical and empirical literature points to a number of factors that are correlated to the probability of receiving a subsidy for R&D. Previous research has found that several firm characteristics, such as age, group membership, size, financial structure, past R&D and innovation efforts or export activity, are correlated with public funding of R&D. Although the studies widely differ in the support programs under analysis, in almost all the studies large firms who planned their innovation activity and had previous R&D experience were the main beneficiaries of subsidies.

In more detail the control variables used in our baseline specifications are the following:#
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Firm size (lagged): Evaluation studies suggest that larger firms are more likely to be subsidized than smaller firms. This is in part due to the positive relationship between firm size and innovation activities which has been extensively debated in the literature (Cohen and Klepper, 1996). In the probit model, firm size is measured as the log of total number of employees.

Firm age: Well established companies, with previous experience in the application process for public funding can be better placed in the competition for public funding. Moreover old firms may have had better opportunities with respect to new and young firms to establish contacts with and influence the support-granting authorities.

Past Innovative Behaviour Indicators: Research has shown that previous innovation activities, proxied by patents or by the presence of R&D departments, are positively related to the probability of being subsidized (Wallsten, 2000; Hussinger, 2008). Previous research activities influence the granting of subsidies because the firms that do the more R&D are the ones that are the most likely to apply for subsidies. It is in fact to be expected that those firms with previous R&D experience which systematically plan their activities, detailing them in a plan, will

[5] Given the structure of our data for *t* has to be intended the years 2001-2003 and for *t-1* the years 1998-2000.

find making the request for subsidies easier. In the model the innovative background is approximated by the percentage of R&D personnel over total employee and by a dummy variable indicating whether the firm introduced any innovation at time t-1 or not.
#
Export activity (lagged): Firms that export their products are usually exposed to strong international competition, and are likely to strengthen their competitiveness through innovation. Furthermore, one of the goals of R&D funding schemes may be to strengthen the competitiveness of firms in international markets. Thus, export activities can represent a signal for the allocation decision of the public R&D funds if policymakers are believed to be inclined to subsidize R&D projects with potentially high international market success (Blanes and Busom, 2004).

Other characteristics of the firm: We have considered other variables that might have an important discriminatory power between subsidised and non-subsidised firms. The relationship of these variables with innovation activities has been widely documented in the literature. In particular, the econometric specifications account for **group membership**, since firm belonging to a group may be better equipped to apply for a subsidy because resources at the corporate level, such as information, expertise and funds, are made available to the applicant; **credit rationing** (proxied by the percentage of firms declaring of having asked for additional funds being denied at t-1); the intensity of **fixed capital investments** measured as the log of fixed capital investments per employee at t-1 as well as **ICT investments**.
As previously claimed, we believe that structural difference may emerge in the working of R&D subsidies between sectors characterized by a different technology intensity. For this reason all models will be tested on the whole sample and on the two sub-samples concerning companies operating in low-tech and high-tech industries.
In the following Table 5 we report the definition of the variables that will be used in the different specifications of the model on the persistence of R&D subsidies.

[Insert Table 5 here]

Building on the results obtained from the probit model previously described it is possible to carry out an impact evaluation analysis on public R&D subsidies. In order to test the effect of public grants (treatment) on the targeted subjects (treated), it has to be taken into account that the receipt of a subsidy is not random, but rather is subject to different selection processes. Among the different methods developed to perform impact evaluation analysis, the approach based on matching techniques has been widely used in recent years (Heckman et al., 1999, Blundell and Costa Dias, 2000; Almus and Czarnitzki, 2003; Hussinger, 2008). In our analysis we follow this approach, which appears to be appropriate with respect to the objectives of the research and the statistical information available. Regarding this latter aspect, four important characteristics of the database used for the empirical analysis appear to be relevant for the effectiveness of the evaluation method adopted (Heckman, Ichimura and Todd, 1998). First, the information on both supported and not-supported firms is provided by the same survey; second, the data contain a rich set of variables on firms' structure and behaviour relevant to modelling the participating decision; third, the goodness of matching is facilitated by the presence of a large number of non-treated companies in the sample; finally, the use of two survey waves allowed us to use lagged variables as controls in the selection equation so that we could reduce problems due to endogeneity.

The crucial research issue in this type of analyses is to measure the effect of public R&D support on firms' innovation performances in the absence of counterfactual evidence, so that it is not possible to forecast the result of firms' innovation performances in the absence of subsidies. The solution that can be adopted in such circumstances is to use the results of non-treated firms, with similar characteristics, to estimate the possible effect on treated companies had they not participated in public funded R&D programmes. The basic idea of the matching is then to balance the sample of subsidy recipients and comparable non-recipients by selecting the best twin from the control group for each subsidized firm, so that the means of the outcome are comparable between the two groups. In this way, the differences in the means of the outcome variable between the treated and the selected control groups (Average Treatment Effect on the Treated – ATT) can be then attributed to the treatment (Rosenbaum and Rubin, 1983; Heckman et al. 1998).

In the ideal case, the best twin for a subsidized firm is the firm which is identical in all relevant characteristics. However, when the number of matching criteria is large, it would be very difficult to find any such observation. A solution to this problem is represented by the "propensity score" matching (PSM) method, proposed by Rosenbaum and Rubin (1983) who demonstrated that it is possible to reduce the multi-dimensionality of the matching procedure through the use of a synthetic mono-dimensional propensity score. The procedure consists in estimating the propensity score which is the probability of accessing R&D subsidies for the whole sample and find pairs of treated and non-treated that have the same probability value of participation. Usually, a 'nearest neighbour' (NN) matching is performed, so that the control observation with the estimated probability value closest to the participant is selected.

The Average Treatment Effect on the Treated (ATT) is only defined in the region of common support, since a major source of evaluation bias arises if the common support assumption is violated (Heckman et al., 1997). Hence, an important step is to check the overlap and the region of common support between treatment and comparison group. We therefore have to impose the restriction that the region of common support lies between the minimum and the maximum of the propensity score of the comparison group and consequently drop in the estimates the treatment observations whose propensity score lies outside this region.

Since we do not condition on all covariates but on the propensity score it is important to check if the matching procedure is able to balance the differences of the relevant variables in both the control and treatment group. In order to assess the quality of the matching we will compare the situation before and after the NN matching and we will check, with two-sample t-tests, if differences after conditioning on the propensity score have been eliminated. Finally, as a further test we will check the robustness of our results by using different matching estimators.

5. Empirical results

Table 6 shows the results for different specifications of the probit model regarding the determinants of firms' access to public R&D subsidies for the whole sample. The same models are tested for the two separate sub-samples of high-tech and low-tech companies (Table 7).

Globally, the predictions of the probit models are good with about 80% of concordant predictions and levels of the likelihood ratio chi-square always suggesting that our models, as a whole, are statistically significant. Results in general show that, even after controlling for a number of firm characteristics, the probability of observing a subsidized company in period t is still positively and significantly affected by its R&D subsidy history. Hence, the models estimated confirm the picture emerged from the analysis on TPMs, highlighting the presence of state dependence in the access of public R&D grants by firms, which, however, turns out to be shaped by specific firms' idiosyncratic characteristics.

The introduction of a number of different control variables allows us to test the robustness of the relationships identified between past and current realization of the dependent variable. Moreover, the significance of other variables entered in the models is most important as it confirms the path dependent character of the non-ergodic persistence. Among the relevant factors, the size of observed companies, their age and the level of R&D capabilities, as measured by the share of internal R&D personnel over total employee, significantly enhance the probability of subsequent access to public R&D subsidies. Since large, experienced firms characterised by relevant R&D competences in the past are more likely to receive public R&D funding, we can interpret this result as evidence that the distribution policy of public agencies favoured firms guaranteeing the technical viability of the subsidised projects.

[Insert Table 6 here]

These results can be qualified further by looking at differentiated patterns that can be observed for different groups of industries as shown in Table 7. Here a clear distinction emerges between companies operating in the two different groups of industries. In the case of low-tech industries, the past access to R&D subsidies is the only variable that appears to matter in every model specifications considered. On the contrary, for the group of firms in high-tech sectors, R&D subsidy history is statistically relevant but with a lower magnitude and other characteristics of companies appear to be important in shaping the probability of accessing subsidies. In particular firms' research capabilities come out as a crucial determinant in the allocation of public resources in this field.

[Insert Table 7 here]

These results are consistent with our research hypotheses and have relevant implications. In both cases Matthew effects apply, but they appear to have a distinct nature. In particular, in low-tech sectors, the dynamics of the process is past dependent where cumulative and self-reinforcing reputational effects dominate whatever firms do along the process. On the contrary, in the case of high-tech sectors the process is path dependent: the past allocation of a public subsidy matters but does not guarantee that the firm will receive a subsidy in subsequent rounds of allocation. When competence-virtuous Matthew effects apply, firms' specific behaviours and characteristics are relevant in shaping committee members perception of the actual technological competence accumulated by applicant companies also as a consequence of previous grants.

Since this distinction is supposed to produce effects in terms of differentiated success of the policy instrument we can test further the result with the impact evaluation analysis based on the Propensity Score Matching method described in the previous section. Table 8 reports the non-parametric estimation results of average treatment effect obtained throw nearest neighbour matching for all the considered models. Results for the whole sample show that after controlling for selection bias the average subsidised firm has significantly greater R&D expenditure per employee compared to a twin-firm not supported by this type of public intervention. This evidence suggests that our data in general support the hypothesis of additionality of R&D subsidies, which do not substitute private R&D investments. Moreover, regarding complementarity effects, the empirical evidence shows that grants do not induce firms to further increase private R&D investment as a response to public funding. As reported in Table 8, firms receiving subsidies are characterised by higher private R&D investments. However, the result is in general not statistically significant, suggesting that differences between granted and non granted firms are ambiguous.

[Insert Table 8 here]

In order to test if differentiated effects of subsidies across groups of sectors operate, we performed the impact evaluation analysis on the two subsamples of companies in high-tech and low-tech industries.

Our results are clear cut and coherent with our hypotheses. All the tested models confirm that in the former group marked signs of additionality emerge from the analysis. Such evidence represents a further indication on the type of Matthew effect here in action, suggesting the prevalence of a virtuous-competence Matthew effect, where cumulability is at work and the persistence of the provision of subsidies is associated with firms that have been actually able to use previous subsidies to effectively increase their overall R&D activities. Conversely, in low-tech industries, additionality in R&D investments is not supported by data suggesting that some substitution mechanism has taken place and that the nature of the identified persistence is mainly perverse.

Different tests have been carried out in order to check for the reliability and robustness of our results. Firstly, we verified that after the matching procedures tests show that all considered variables are balanced in both groups, with the matching strongly reducing the bias of the matched groups with respect to the unmatched groups[6]. We further test the robustness of our results by using different matching estimators (See Table 9). First, we implemented a *Caliper* matching, which avoids the risk of bad matches if the closest neighbour is distant. Finally, since the NN matching is a one-to-one technique and discards data that are potentially valuable, we performed a *Kernel* estimator, which makes it possible to match each treated with more than one comparable non-treated. In this last case we also used bootstrapped standard errors, so that the estimated variance of the treatment effect include the variance due to the derivation of the propensity score, the determination of common support and the order in which treated individuals are matched. The bootstrapping is based on 50 replications of the original sample. As shown in Table 9 our results are robust to different model specifications and different matching techniques adopted.

[Insert Table 9 here]

6. Conclusions and policy implications

The present paper has investigated the occurrence and the causes of persistence in the provision of public subsidies by means of discretionary allocation procedures. In particular, it articulated the notion of Matthew effect by distinguishing between *virtuous* and *vicious*. The former consists in the persistence of the provision of subsidies to firms that have been actually able to use previous subsidies to effectively increase their competence, their internal stock of technological knowledge and the flows of current R&D activities. The latter concerns the cases of persistence in the assignment of public subsidies based on sheer reputation, even to firms that have actually reduced their commitment to research after receiving previous subsidies. Moreover, it has been argued that such a distinction is relevant in the analysis of the allocation mechanisms and of the effects of subsidies in different groups of industries characterized in terms of their technological intensity.
The relevance of these arguments has been tested by implementing a rich strategy of empirical analysis based on the exam of transition probabilities between states, the development of an original model on the determinants of firm's access to R&D grants and on an evaluation impact analysis adopting Propensity Score Matching methods. Both the descriptive and econometric evidences show that past grants increase the probability to access further funding and suggest that the access to public subsidies for R&D activities is indeed characterised by significant persistence. However, such a persistent character of R&D subsidies is not necessarily dysfunctional, but produces differentiated effects across sectors. In particular, the empirical analysis provides evidence on the working of a positive persistence, i.e. *virtuous* Matthew effects in high-tech industries, while signals of perverse effects are

[6] We have omitted the table for reasons of space. Results of the tests are available from the authors on request.

observed in low-tech sectors. Our paper has shown that the basic critique of the discretionary allocation procedures according to which past recipients have disproportionate access to public support with respect to other firms that never received such a grant applies only and mainly in low-tech industries with low levels of knowledge cumulability. In such a case the persistence in the allocation of such grants can be interpreted as a reliable signal that perverse relations take place and exclude other firms less able to sneak in these complex bureaucratic procedures. Perverse learning processes, exclusively based upon the better understanding by recurrent recipients of the working of the selection committees and the passive compliance of their members to reputational effects do impede, in these industries, the correct allocation of public funds to support R&D activities

These results have important implications for designing and implementing targeted innovation policies. The characteristics of knowledge as an economic good provide the basic rationale to advocate the public support of research activities. The identification and appreciation of the key role of knowledge cumulability provide a major opportunity for innovation policy to foster the rates of generation of technological knowledge on two counts. First, when knowledge cumulability matters the likelihood that beauty contexts allocation procedures are able to stir virtuous Matthew effects with positive feedbacks are higher. Second, the selective support of R&D activities characterized by high levels of knowledge cumulability can actually yield positive results that go beyond the classical remedy to knowledge market failures so as to become a strategic tool to direct and implement the supply of technological knowledge in an economic system. Beauty context allocation of public subsidies can become part of a wider industrial policy aimed at implementing and exploiting the complementarities among the research projects of the individual firms so as to strengthen their coherence at the system level (Mohen and Roller, 2005).. Finally, the implications of our results are most important as they provide the foundation to support the implementation of discretionary procedures for the allocation of selective subsidies to research projects mainly in high-tech industries. Automatic public incentives might apply in the rest of the economic system where knowledge cumulability is less relevant.

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TABLES

Table 1 The effects of Matthew dynamics

	Path Dependence	**Past Dependence**
	Virtuous Matthew Effect	*Vicious Matthew Effect*
Inclusive Matthew Effect	Picking true innovators with high levels of knowledge cumulability and able to take advantage of learning to learn that increase both the total R&D budget and the flows of innovations	Persistent inclusion of past occasional innovators that substitute private funds with public ones because of low levels of knowledge cumulability
Exclusive Matthew Effect	Exclusion of Phoney Innovators	Hungry Orphans

Table 2 Summary statistics for the sample (years 2001-2003).

	Total Sample		Access to R&D Subsidies			
			Yes		No	
	Mean	**st dev**	**Mean**	**St. dev.**	**Mean**	**St. dev.**
Number of employees	139.69	520.35	222.06	948.21	115.63	293.08
R&D per employee (Euro)	3308.51	4896.34	5241.93	6396.20	2743.76	4204.22
Share of employees in R&D (%)	8.46	8.96	11.06	9.72	7.71	8.59
Turnover (MEuro)	39.04	271.85	59.08	344.61	33.19	246.64
Fixed capital investments/Emp. (Euro)	5334.325	6506.06	5582.54	6369.79	5261.82	5648.95
Export	83.00%		85.12%		82.38%	
Access to R&D Subsidies (1998-2000)	13.56%					
Access to R&D Subsidies (2001-2003)	22.61%					
Number of firms in high-tech sectors	354					
Access to R&D Subsidies (2001-2003) high-tech sectors	26.84%					
Number of firms in low-tech sectors	398					
Access to R&D Subsidies (2001-2003) low-tech sectors	18.84%					

Table 3 Transition probabilities between period T and T-1 along years 1998-2003. Full sample.

T-1 \ T	Yes	No
Yes	0.451 (0.0493)	0.549 (0.0493)
No	0.191 (0.0154)	0.809 (0.0154)

Standard Errors in parentheses

Table 4 Transition probabilities between period T and T-1 along years 1998-2003 in High-Tech and Low Tech industries.

	T-1 \ T	Yes	No
High-Tech group	Yes	0.422 (0.0617)	0.578 (0.0617)
	No	0.234 (0.0249)	0.766 (0.0249)
	T-1 \ T	Yes	No
Low-Tech group	Yes	0.500 (0.0811)	0.500 (0.0811)
	No	0.156 (0.0191)	0.844 (0.0191)

Standard Errors in parentheses

Table 5 Definition of variables.

R&D_SUB	Dummy variable that equals one if the company has access to public R&D subsidies
SIZE	Log of the number of employees
INNOV	Dummy variable that equals one if the company performs any innovation activity
R&D_EMP	Share of R&D personnel over total employee (%)
EXPORT	Dummy variable that equals one if the company exports
INV_EMP	Log of the fixed investments per employee performed by the company
ICT	
GROUP	Dummy variable that equals one if the company belongs to a group
CRED_RAT	Dummy variable that equals one if the company declared having asked for credit being denied
DEG_EMP	Share of personnel with university degree over total employee (%)
AGE	Company's age.

Table 6 Probit model. Dependent variable: Access to public R&D subsidies (R&D_SUB)

	(1) Model I	(2) Model II	(3) Model III
R&D_SUB (t-1)	0.63***	0.63***	0.64***
	(0.144)	(0.144)	(0.145)
AGE	0.01*	0.01*	0.01*
	(0.003)	(0.003)	(0.003)
SIZE (t-1)	0.09*	0.09*	0.09
	(0.053)	(0.055)	(0.055)
R&D_EMP (t-1)	0.01***	0.01**	0.01***
	(0.006)	(0.006)	(0.006)
CRED_RAT (t-1)	-0.07	-0.07	-0.07
	(0.140)	(0.140)	(0.141)
GROUP (t-1)	-0.05	-0.05	-0.04
	(0.130)	(0.130)	(0.130)
INV_EMP (t-1)	0.00	0.00	0.00
	(0.016)	(0.016)	(0.016)
EXPORT (t-1)		-0.01	-0.00
		(0.146)	(0.146)
INNOV (t-1)		0.01	0.02
		(0.123)	(0.123)
ICT_EMP (t-1)			-0.01
			(0.006)
Constant	-1.44***	-1.44***	-1.43***
	(0.220)	(0.235)	(0.235)
N. of firms	752	752	752
LR Chi-sq.	42.66***	42.67***	44.46***

Standard errors in parentheses(***, **, *: significant at the 99%, 95%, 90% level)

Table 7 Probit model. Dependent variable: Access to public R&D subsidies (R&D_SUB)

	LOW-TECH INDUSTRIES			HIGH-TECH INDUSTRIES		
	(1)	(2)	(3)	(4)	(5)	(6)
VARIABLES	Model I	Model II	Model III	Model I	Model II	Model III
R&D_SUB (t-1)	0.99***	0.96***	0.97***	0.36*	0.36*	0.37**
	(0.227)	(0.228)	(0.228)	(0.191)	(0.191)	(0.192)
AGE	0.00	0.00	0.00	0.01*	0.01*	0.01*
	(0.004)	(0.004)	(0.004)	(0.004)	(0.004)	(0.004)
SIZE (t-1)	0.05	0.05	0.05	0.15**	0.13*	0.13*
	(0.079)	(0.083)	(0.083)	(0.075)	(0.077)	(0.077)
R&D_EMP (t-1)	0.01	0.01	0.01	0.02**	0.02***	0.02***
	(0.010)	(0.010)	(0.010)	(0.008)	(0.008)	(0.008)
CRED_RAT (t-1)	-0.29	-0.33	-0.32	0.17	0.18	0.18
	(0.205)	(0.207)	(0.207)	(0.202)	(0.203)	(0.203)
GROUP (t-1)	-0.14	-0.13	-0.13	-0.03	-0.01	0.01
	(0.192)	(0.193)	(0.193)	(0.182)	(0.183)	(0.184)
INV_EMP (t-1)	0.01	0.01	0.01	-0.01	-0.00	0.00
	(0.021)	(0.022)	(0.022)	(0.024)	(0.025)	(0.026)
EXPORT (t-1)		-0.20	-0.19		0.28	0.29
		(0.189)	(0.190)		(0.244)	(0.244)
INNOV (t-1)		0.11	0.11		-0.17	-0.16
		(0.169)	(0.170)		(0.188)	(0.188)
ICT_EMP (t-1)			-0.00			-0.01
			(0.011)			(0.008)
Constant	-1.26***	-1.19***	-1.18***	-1.63***	-1.78***	-1.76***
	(0.309)	(0.320)	(0.320)	(0.331)	(0.377)	(0.378)
N. of firms	398	398	398	354	354	354
LR Chi-sq.	25.30***	26.69***	26.74***	21.55***	23.48***	25.15***

Standard errors in parentheses(***, **, *: significant at the 99%, 95%, 90% level)

Table 8 Estimation of the ATT with the Nearest Neighbour Matching method.

All Industries	Model	Mean		Difference	t-test
		Treated	Control		
Outcome Variable					
R&D /EMPLOYEE	I	5241.9	3404.8	1837.2	2.75
PRIVATE R&D /EMPLOYEE	I	3751.8	3294.6	457.2	0.73
R&D /EMPLOYEE	II	5241.9	2949.0	2292.9	3.42
PRIVATE R&D /EMPLOYEE	II	3751.8	2846.9	904.9	1.45
R&D /EMPLOYEE	III	5241.9	2385.5	2856.4	4.51
PRIVATE R&D /EMPLOYEE	III	3751.8	2315.7	1436.0	2.43
Low-Tech Industries					
R&D /EMPLOYEE	I	3754.3	3100.3	654.0	0.66
PRIVATE R&D /EMPLOYEE	I	2414.0	2911.0	-497.1	-0.52
R&D /EMPLOYEE	II	3754.3	2927.0	827.3	0.86
PRIVATE R&D /EMPLOYEE	II	2414.0	2759.5	-345.5	-0.38
R&D /EMPLOYEE	III	3754.3	3304.0	450.2	0.52
PRIVATE R&D /EMPLOYEE	III	2414.0	3192.6	-778.5	-0.83
High-Tech Industries					
R&D /EMPLOYEE	I	6416.4	3791.7	2624.7	2.57
PRIVATE R&D /EMPLOYEE	I	4808.0	3654.1	1153.9	1.22
R&D /EMPLOYEE	II	6416.4	3843.4	2573.0	2.63
PRIVATE R&D /EMPLOYEE	II	4808.0	3793.2	1014.7	1.11
R&D /EMPLOYEE	III	6416.4	3718.7	2697.7	2.87
PRIVATE R&D /EMPLOYEE	III	4808.0	3503.8	1304.7	1.48

Table 9 Robustness Checks: Estimation of the ATT with the Nearest Neighbour Matching with Caliper and with Kernel method (Bootstrapped S.E.)

Matching Method		Nearest Neighbour with Caliper		Kernel with Bootstrapped S.E	
All Industries	**Model**	**ATT**	**t-test**	**ATT**	**z-test**
Outcome Variable					
R&D /EMPLOYEE	I	1733.9	2.60	1879.6	3.80
PRIVATE R&D /EMPLOYEE	I	374.7	0.60	538.7	0.97
R&D /EMPLOYEE	II	2195.1	3.29	1878.9	3.18
PRIVATE R&D /EMPLOYEE	II	827.8	1.32	537.9	1.21
R&D /EMPLOYEE	III	2765.3	4.39	2081.5	3.55
PRIVATE R&D /EMPLOYEE	III	1365.2	2.31	720.1	1.32
Low-Tech Industries					
R&D /EMPLOYEE	I	738.9	0.76	809.4	0.96
PRIVATE R&D /EMPLOYEE	I	-466.7	-0.50	-434.4	-0.59
R&D /EMPLOYEE	II	735.8	0.80	1066.1	1.58
PRIVATE R&D /EMPLOYEE	II	-412.4	-0.47	-245.7	-0.41
R&D /EMPLOYEE	III	384.0	0.43	998.2	1.23
PRIVATE R&D /EMPLOYEE	III	-972.0	-1.15	-313.6	-0.48
High-Tech Industries					
R&D /EMPLOYEE	I	2659.7	2.65	2205.3	2.57
PRIVATE R&D /EMPLOYEE	I	1187.8	1.28	805.9	1.13
R&D /EMPLOYEE	II	2298.8	2.31	2455.7	2.87
PRIVATE R&D /EMPLOYEE	II	821.4	0.88	1096.3	1.47
R&D /EMPLOYEE	III	2568.5	2.71	2514.3	2.83
PRIVATE R&D /EMPLOYEE	III	1110.6	1.24	1151.3	1.45