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An overall evaluation of public R&D subsidy on private R&D expenditure in absence or in combination with R&D tax credit incentives

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Abstract

This study analyzes the effect of public R&D subsidy on private R&D expenditure in a sample of French firms during the period 1993-2009. We evaluate whether there is input additionality of public R&D subsidy by distinguishing between R&D tax credit recipient and non-recipient firms, i.e. we test the complementary of such policy tools. In addition, combining difference-in-differences with propensity score and exact (both simple and categorical) matching methods, we assess the effect of R&D subsidy between treated (subsidy recipients) and controls (subsidy non-receipients) as well as between differently treated (small, medium and large subsidy recipient) firms. Furthermore, we implement a dose-response matching approach to determine the optimality of public R&D subsidy provision. We find extensive evidence of either no additionality or substitution effects between public and private R&D expenditure.

Additionality or crowding-out? An overall evaluation of public R&D subsidy on private R&D expenditure in absence or in combination with R&D tax credit incentives.

Abstract

This study analyzes the effect of public R&D subsidy on private R&D expenditure in a sample of French firms during the period 1993-2009. We evaluate whether there is input additionality of public R&D subsidy by distinguishing between R&D tax credit recipient and non-recipient firms, i.e. we test the complementary of such policy tools. In addition, combining difference-in-differences with propensity score and exact (both simple and categorical) matching methods, we assess the effect of R&D subsidy between treated (subsidy recipients) and controls (subsidy non-receipients) as well as between differently treated (small, medium and large subsidy recipient) firms. Furthermore, we implement a dose-response matching approach to determine the optimality of public R&D subsidy provision. We find extensive evidence of either no additionality or substitution effects between public and private R&D expenditure.

JEL Classification: C14, H50, 038.

Keywords: R&D subsidy; R&D tax credit, optimal provision of public R&D support.

1 Introduction

The positive relationship between R&D investment and economic growth is well rooted in economic theory and, on this nexus, policies fostering private R&D investments are regarded as growth-conducive and therefore as desirable from a social point of view.

But it is also on a mere efficient ground that these policies are viewed as necessary in a market economy. The incomplete appropriation of the returns to R&D that arises - a form of negative externality - inevitably leads to a deficient level of R&D investment - a market failure. The role of public policy is then to propel private R&D investment to a social optimal level. This role could not be more apparent than in the recent economic crisis. As noted by the OECD (2013), many governments have adopted a number of measures aiming at supporting firms' innovation. These measures reflect the conviction of policy makers that an adequate level of innovation is not only crucial to business success, but it is also a decisive factor to recover from the downturn. Yet - even if governments allocate public resources in favor of those projects that would not have been realized in absence of public support (crowding-in or additionality),¹ it is plausible that eligible firms simply substitute R&D investments they originally planned to undertake with the public financial resources made available (crowding-out), undermining the argument for "additional" effects of public aid. In our sample, for instance, firms, which receive the largest subsidies, are also those exhibiting the lowest R&D intensity. To strike a balance between "crowding-in" and "crowding-out" effects that typically plague such public policies, policy makers are assigned the tasks of designing (i) the eligibility criteria allowing a firm to benefit from a public R&D grant, (ii) the modulation of public intervention, and (iii) the optimal policy mix to achieve defined technology policy objectives.

Considerable volumes of resources are spent each year in the R&D public funding and, not surprisingly, the academic debate has focused on the analysis of those policies and, in particular, on the assessment of their effectiveness. Evaluating the extent of the economic payoff of a public grant to R&D is basically an empirical question, but assessing its impact is a challenging task. The main problems are due to the difficulties faced a) in controlling for the high selection bias, b) in discriminating the potential different effects of induced by heterogeneous treatment levels provided to firms through the R&D public subsidy, and c) in isolating the effects of the subsidies from the other confounding factors such as the contextual implementation of other R&D policies, that can affect the goals defined by the policy makers, as well as any variables unobservable to the econometrician that, if not properly taken into account, can be a serious source of estimation bias.

The numerous evaluation studies in this field (e.g. Lach, 2002; Almus and Czarnitzki, 2003; Gonzalez and Pazo, 2008) have implemented techniques aimed to account for the selection bias but have not included

¹For the use of this terminology - "crowding-in" - see Diamond (1999), p. 424.

extensive considerations relative to the role played by the other cited factors. Specifically, the existing literature has usually applied single-treatment frameworks to the R&D subsidy evaluation exercises. Nevertheless, when it turns to assess the impact of a public R&D grants on firms' R&D investments, it is reasonable to assume that it is not only the mere provision of an R&D public grant but also how much it is granted to a firm that may matter. Incorporating these aspects into any R&D policy analysis is imperative especially in a time of limited public budgets. Moreover, evaluating the impact of public subsidies to business R&D without taking into account the interactions and interdependencies with other R&D policies, which affect the extent to which policy goals are realized, may lead to misleading conclusions on the ultimate effectiveness of the policy tool under study. As argued by Guerzoni and Raiteri (2014) the presence of R&D policies other than the one under analysis, may act as "potential hidden treatments" that can affect firms' R&D expenditure. The availability of data on contextual R&D policy instruments is a prerequisite in order to control for the joint impact of contextual R&D policies, and the absence from the R&D surveys – the main data sources in this kind of studies – of details on this matter, can be identified as the main justification of this existing gap in the literature.

Different from many existing studies, our empirical analysis aims at addressing these concerns. We argue that an overall assessment of public grant support to R&D activities should evaluate not only the advisability of public support, but also its modulation as well as the presence of other unobserved contextual factors (among which the contextual presence of different R&D policy tools is the most obvious), equally important aspects, yet under-studied in this literature.² Thus, to make a step toward this ultimate goal we evaluate the modulation of public R&D subsidy by means of a difference-in-differences (DID) technique combined with several (propensity score, exact and continuous treatment) matching methods. In addition, we control for the potential complementarity of another relevant public policy tool such as the R&D tax credit. Our interests in studying the R&D subsidy under the R&D tax credit are explained by several factors. Firstly, they are the two most popular policy instruments adopted in the context of many national technology policies aimed at stimulating firms' innovative profiles. Secondly, although public R&D subsidy and tax credit are distinct schemes, policy makers often view them as complements. The combination of these tools is however heterogeneous: whereas some R&D intensive economies have decided not to implement any R&D tax credits (e.g. Finland, Germany, Sweden and Switzerland), tax credit dominates the direct R&D funding among OECD countries with generous public support to R&D (e.g. Canada, France and South Korea) as reported in OECD (2011). Lastly, being the present analysis aimed at assessing the effectiveness of the French public R&D subsidy system, any conclusions that disregard the prominent role of the French R&D tax credit, would be incomplete.

²See Blundell and Costa Dias (2000) and Aerts and Schmidt (2008).

To investigate the implications of the modulation of public R&D subsidy along different dimensions, we divide recipient firms into a number of groups defined in terms of the percentile (tercile) of the public subsidy received. First, we simply consider how different (small, medium or large) amounts of R&D grants impact on the advisability of public R&D. By comparing R&D outcomes between similar funded and not funded firms or between similar but differently funded firms, we can establish which groups of recipients are mainly contributing to the growth of R&D investment in the economy. The outcome variables we look at are both the level and the percentage change of the private R&D expenditure. By looking at the latter, we avoid any potential bias due to time-invariant firm specific factor that the available data do not allow to control for. Furthermore and more importantly, matching firms on their pre-treatment characteristics in each observational year, we deal with time-varying unobservables affecting the treatment and the outcome variables simultaneously.

Second, we study the adequacy of the allocation of subsidies to firms' R&D activities. Employing a categorical treatment evaluation scheme we compare publicly financed firms with similar characteristics across different groups. Our econometric exercise is implemented by combining both propensity score and exact matching technique. Whereas the former is computed on all observables, the latter allows us to further strengthen the precision of the comparison by fixing an exact matching among a number of categories (e.g. firm size, industry, past recipient status). The policy relevance of these comparisons is hard to question, as it is needed to determine whether firms benefiting from the largest amounts of public funding are also investing more in R&D. If this is not the case, then public authorities may improve their policy targeting through funds re-allocation among recipients.

Third, we turn to the question of determining the proper modulation of R&D public financing. By means of the continuous (dose-response) treatment matching scheme, we can evaluate the effect of further increasing the public grant on private R&D expenditure, as this method can identify the marginal effects of subsidies and their optimal amounts. The amount at which the public support ceases to be beneficial can therefore be determined.

Fourth, we do not test the effects of the R&D subsidy in isolation only, but we test the impact of the R&D subsidy under the provision of tax credits to R&D performers. Specifically, R&D subsidy recipients are compared with non-recipients as well as with firms benefiting contextually from R&D subsidy and R&D tax credit.

Finally, by taking advantage of an unusual characteristic of the R&D national policy in France that created the conditions for a policy change – notable discontinuities in the average R&D tax credit clearly emerge in 2004 and 2008, which have been the years of major reshaping of this policy tool by the French authorities – we can strengthen the causal interpretation of our findings by incorporating considerations relative to the

exploitation of exogenous variations in the public R&D provision.

Our empirical analysis shows that a notable substitution between private and public funds occurs, especially for high level of the public subsidy. Recipients of larger doses do not outperform recipients of lower doses or even non-recipient firms. The substitution becomes more apparent when we analyze the intra-tercile distribution of public funds under tax credit: we highlight a considerable reduction in growth of private R&D expenditure among the top beneficiary companies. Specifically, it emerges - on average - that funded firms receiving subsidies up to 400 thousands Euros exhibit a low private contribution with respect to their counterfactual units. Overall these results indicate that an ex-post evaluation of the targets of a R&D policy is desirable, if not necessary in time of downturns. In fact, if R&D funding has to become a valid policy instrument to support companies hardly hit by a crisis and facing financial restrictions, it is inevitable that public resources should not be re-directed away from risky and promising long-term research projects toward the big players who would perform equally well without these funding.

The remainder of this paper is structured as follows: section 2 briefly reports the literature and institutional background, section 3 summarizes the data and variables, section 4 describes the main econometric techniques we make use of, section 4 reports our main findings and robustness checks, and section 5 offers concluding remarks.

2 Previous studies and institutional background

2.1 Previous studies

The empirical literature concerned with the evaluation of R&D policies has typically relied on the notion of additionality as an indicator of policy effectiveness. The concept of “additionality” was introduced by Buisseret et al. (1995) and indicates the difference made by the state interference in the market play. The argument can be summarized as follows: economic theory and empirical findings robustly support the positive relationship linking R&D investment and economic growth. Then, assuming that public aid for technological developments induces private firms to undertake “additional” R&D investments (i.e. firms that would have not undertaken those R&D investments without public support), it is possible to infer that the policy intervention leads to economic growth and social welfare. To address the inquiry of “additionality,” evaluations of public financing programs typically present casual analyses based on counterfactuals, what would have occurred in absence of intervention. At the heart of this analysis is the recognition that neither firms, which have received support nor firms, which have not applied for funds can be considered random events. On the contrary, firms’ behavior is the explicit consequence of the policy design, as firms are often aware of those

criteria on the basis of which governmental authorities will decide funds allocation (i.e. self-selection). In this respect, our study is no exception and follows this strand of literature, assessing the French R&D grant support system performing an “after the fact” analysis as in Almus and Czarnitzki (2003), Blanes and Busom (2004), Czarnitzki and Licht (2006), González and Pazó (2008), Hussinger (2008), among the others.

It is undeniable that a plethora of studies implementing different approaches and overcoming database limitations in different ways has generated a vast mixed evidence, ranging from being in favor of “crowding-in” effects (Görg and Strobl, 2007; Aerts and Schmidt, 2008; Hussinger, 2008) to being unable to reject “crowding-out” effects (Lach, 2002; Heijs and Herrera, 2004).³ Our study is partly related to Görg and Strobl (2007) and Guerzoni and Raiteri (2014). Görg and Strobl (2007) implement the categorical matching, but neglect - one of our salient contributions - the continuous treatment approach in evaluating the effects of R&D promoting policies. But, content-wise, the outcome we consider, the private R&D expenditure, is different from the outcome they focus on, the engagement of firms on international markets. Guerzoni and Raiteri (2014) argue that the framework created by the matching methodologies can suffer from serious limitations due to unobserved variables that can act as potential confounding factors in the analysis. In particular, their focus concerns the role played by other R&D policies that if remain unobserved can act as “hidden treatments” on the outcome variable and lead to biased estimations. To cope with this issue they however use only a standard matching technique, in which three R&D policy instruments (i.e. R&D subsidy, innovative public procurement and R&D tax credit) are considered as treatment variables and evaluated first in isolation and then in combination with each other.

Similar to Guerzoni and Raiteri (2014), we also focus on the effectiveness of R&D investment incentives among R&D tax credit recipients and non-recipients. Compared to R&D subsidies, the political success of R&D tax credit is based on its supposed neutrality and actual flexibility. The former feature is due to the fact that in theory all firms are entitled to benefit from such a scheme irrespective to their characteristics. In practice, and here comes the latter feature, R&D tax credit schemes can potentially be targeted to specific groups of firms, according to their size, age, location, link with academic labs, and technology (see Lhuillery, 1996; Duguet, 2012; OECD, 2010). Indeed, the attractiveness of R&D tax schemes originates also from their easy implementation: they do not present issues associated with the lack of information on innovators, cost of bureaucratic procedures, and potential lobbying pressures that are typically involved into subsidy allocation. Conversely, the provision of R&D subsidies might be preferred to R&D tax credits because through the former it is possible to discriminate among projects and therefore finance the most innovative firms, with obvious consequences in terms of social welfare. Further, R&D subsidies seem to be more suitable than

³See also David et al. (2000), Garcia-Quevedo (2004), Aerts and Czarnitzki (2004, 2006), Almus and Czarnitzki (2003), Czarnitzki and Fier (2001), Duguet (2004), Gonzalez et. al (2005), Gonzalez and Pazo (2008), Lööf and Heshmati (2005), Busom (2000), Suetens (2002), and Wallsten (2000).

tax credits to counteract the effects of business cycle, especially in downturns when firms with stringent budgetary constraints simply cut their private R&D expenditure.

2.2 Institutional background

The French public R&D funding system is particularly apt for the empirical evaluation proposed in this study. France is among the European countries with the highest budget devoted to the distribution of public R&D financing towards private companies. Public authorities implement both direct and indirect R&D policy instruments for business R&D. Since the early 1990s the French government issued several reforms, whose goal has been the creation of a proper framework for boosting innovation. R&D public resources have been distributed on the basis of predetermined criteria such as the level of risk and innovativeness of the proposed projects; promotion of university-firm collaborations; support of new high-tech firm formation, especially when associated with young innovative entrepreneurial projects. Moreover, in order to reach the Lisbon target of R&D spending (at least 3% of GDP), since 2004 a substantial portion of public funding (with annual investments of EUR 450 million) has targeted the “Pôles de compétitivité,” which comprises dynamic and competitive regions of France, particularly focused on the investments in advanced technological areas such as biotechnology and nanotechnology. This policy change made available R&D grants for projects designed to boost collaborative R&D networks (favoring technological transfer as well as other entities such as Public Research Organizations).

The year 2004 has been characterized by a further and probably more impressive reform of the French public R&D funding system, related to the R&D tax credit. Up until 2004 the French tax credit was an incremental tax credit scheme set at the 50% rate and defined as follows: $[0.5 * (R\&D_t - R\&D_{t-1})]$. In 2004 this policy tool has been re-defined as a combination of level and incremental tax credit: $[0.65 * (R\&D_t) + 0.45 * (R\&D_{t-1} - R\&D_{t-2})]$,⁴ in the spirit of the R&D tax credit adopted in other countries such as Japan, South Korea, Portugal and Spain. The ceiling of around EUR 0.5 millions in 1983 (1993?), reached EUR 8 millions in 2004. Within this tax credit regime, firms were allowed to record a negative tax credit. It implied that firms could carry their positive R&D tax credit forwards. This practice has characterized systematically large (R&D) businesses, whereas small and medium enterprises (SMEs) with limited R&D expenditures have faced difficulties in spreading over years the negative tax credit amounts. To deal with this issue, an “amnesty” concerning the negative R&D tax credit has been implemented in 1993 and in 1999. Since 2004, this kind of amnesty has become systematic: negative tax credits could not be carried longer

⁴The balance between the level and the incremental components was subsequently modified in 2006 with 10% and 40% rates, respectively. Further changes have also been introduced since 2008: the regular 30% rate has been applied up to EUR 100 million and dropped to 5% beyond this threshold. However, firms applying for the first time could benefit from a 50% rate in the first year and a 40% in the second year.

than 5 years. The 2007-2009 financial and economic crisis, followed by limited credit availability to SMEs, created a deeper awareness of the increasingly important role of innovation for the revitalization of trade and business activities. The dramatic GDP decline was followed by a substantial drop in long-term investments (OECD, 2012; Filipetti and Archibugi, 2011; Archibugi et al., 2013), leading to an erosion of many countries' innovation capacity. Thus, R&D incentives have been in the policy spotlight as means of alleviation of the recent economic downturn also in France,⁵ where the government allowed public R&D spending to rise, in spite of budgetary pressures from rising deficits and debts. Specifically, in 2008 it was decided to eliminate the existing ceiling for the French R&D tax credit with the objective of pushing firms to invest more resources in R&D activities.

3 Methodology

This section briefly discusses the estimation strategies implemented in our empirical assessment of public R&D subsidies in absence or combination of tax credit policies. Taking advantage of recent advancements in the program evaluation analysis, we have combined the categorical (both pscore and exact version) and continuous (dose-response) treatment matching schemes. The inclination to reduce biases arising from non-random assignments makes these methods widely used in the field of causal inference in observational studies. To provide some insight into the methodology as well as to discuss the strengths and the weaknesses of each method, we discuss them separately.

3.1 Categorical Treatment Matching

It is tautological that the final R&D spending will depend on the amount of the public support received by a firm. But coupling the information on the R&D support receipt by a firm with the information on the amount received opens the prospective of an analysis based on the categorical treatment matching. The categorical (propensity score and exact) matching evaluates the expected class of treatment a firm may receive given the pre-treatment variables. Consistent with the rationale of the dichotomous matching, the estimation of the public intervention impact is based on the comparison of firms with similar scores (and given some exactly similar pre-treatment characteristics in the exact matching), but belonging to two different classes or categories. In our study, these categories are defined by looking at the terciles of the distribution of public R&D funding. It surely represents an objective rule and therefore it is not subject to fully arbitrary and potentially misleading categorization criteria. This estimation method is well suited for comparisons not

⁵Academic articles on this matter empirically show that government transfers and subsidies became substantially more countercyclical (Galí, 1994) and increasing public investments in R&D were invoked. The crucial role of R&D public financing was therefore justified not only in light of the cited market failure argument but also because of the pro-cyclical character of private R&D investments.

only between two consecutive categories of treated groups, but also between treated and untreated (which is not allowed in the continuous treatment case) groups. It helps a lot in understanding whether a given effect obtained from the single-treatment framework is simply driven by a single category of treated or it is concretely confirmed for all categories, i.e. the homogeneity of treatment in the last case may represent a more plausible and acceptable assumption than in the simple dichotomous matching.

Thus, we have the outcome $\{Y^0, Y^1, \dots, Y^M\}$ of $M+1$ different mutually exclusive treatment categories (the 0-category is exclusively composed of untreated). Obviously, we can observe only a realization of the potential outcome vector, the remaining M are counterfactuals. In order to estimate the different treatment effects, the unconfoundedness and common support assumptions must be satisfied. Given the covariates, whereas the unconfoundedness requires the treatment indicator to be independent of the realized outcomes, the common support ensures to find a counterpart in the comparison group, which is addressed by the computation of the propensity score. In this regard, a practical suggestion is that the existence of differently treated units can be ignored in a given pairwise category comparison since they are not needed for identification purposes.

For the implementation of the categorical matching, it is needed to run as many probit estimations as the number of effects we are interested in. So, once identified the probability of receiving a given subsidy or tax credit size compared with the next larger one, conditional on the set of pre-treatment covariates, it is possible to compute the associated treatment effect. Counterfactuals are selected by using the caliper method (set at 0.01). That represents a scalar defining the boundary of the neighborhood in which matching is allowed. In this way, we seek to ensure the quality of matching, since ‘bad’ matches are prevented to be included in comparison groups.

3.2 Continuous Treatment Matching

The implementation of the continuous treatment matching allows us to compare enterprises exposed to a specific level of treatment with ‘matched’ less and more exposed ones, and then to identify marginal effects on firms’ private R&D investment. The treatment group is alternatively composed of firms receiving public R&D funding only or those benefiting from a combination of both R&D subsidy and R&D tax credit. The control group is defined as the set of firms performing R&D but not receiving any form of public support to foster their innovation activity.

The continuous treatment approach turns to be particularly helpful when the number of treatment values is relatively large since as pointed out by Imbens and Wooldridge (2009), the possibility of smoothing across treatment permits to improve the precision of the inference. This estimation strategy is based on key assumption named weak unconfoundedness, formulated by Imbens (2000), which requires only the pairwise

independence of the treatment with each (not joint) of the potential outcomes. In this way, it overcomes one of the limitations of the so-called conditional independence assumption (CIA) made by Rosenbaum and Rubin (1983) for the binary case. Thus, the problems of bias removal and drawing causal inferences can be solved by adjusting for pre-treatment differences. Based on pre-treatment variables, it is possible to compute the conditional probability of receiving a specific level of treatment (not just receiving it), which takes the name of General Propensity Score (GPS). An important property comes for the fact that the weak unconfoundedness given all pre-treatment characteristics implies weak unconfoundedness given the GPS, so the average treatment effects can be obtained by conditioning just on the GPS (Hirano and Imbens, 2004).

More formally, we define (a) a vector of pre-treatment characteristics $X_{i,t-1}$ for each firm i , (b) a set of continuously distributed treatment values $D_{i,t}$ and (c) the dose-response function $F_{i,t}(d)_{d \in D}$. Moreover, we assume $X_{i,t-1}$, $D_{i,t}$ and $F_{i,t}(d)_{d \in D}$ having common probability space. For the sake of simplicity, the subscripts will no longer be reported. Thus, the propensity to obtain the R&D support and the GPS are defined respectively as

$$r(d, x) = Y_{D|X}(d|x) \quad \text{and} \quad R = r(D, X) .$$

Furthermore, the GPS is required to respect the following balancing property condition

$$X \perp 1(D = d) | r(d, x) ,$$

where $1(\cdot)$ is the indicator function.

As explained in details by Bia and Mattei (2008), the implementation of the GPS matching method consists mainly of three steps. In the first one, the score R is estimated and the treatment D (or a monotone transformation of it), given the covariates, is required to respect a normal distribution:

$$g(D)|X \approx N [(\gamma, X), \sigma^2] .$$

Here, $g(D)$ is a suitable transformation of the treatment variable and (γ, X) is a function of covariates with linear and higher-order terms, which depends on a vector of parameters γ . In the second step, the conditional expectation of the outcome variable Y , given D and R , is modelled as follows:

$$E(Y|D, R) = a_0 + a_1D + a_2D^2 + a_3D^3 + a_4R + a_5R^2 + a_6R^3 + a_7DR ,$$

where the power of the arguments can be even higher than 3 and parameters are estimated by OLS. This procedure is useful to exclude that the explicative variables induce any bias while no direct meaning

is attributed to their relative coefficients. Finally, the third step consists of averaging the estimated dose-response function $E(\hat{Y})$ over the estimated score function \hat{R} evaluated at the desired level of treatment.

However, a general drawback of the our matching analysis has roots in the almost impossible exact identification of the decision rule adopted by public authorities. The typical omitted variable issue here arises since we may miss variables (in our data set) that the public actor uses for the attribution of the subsidies. Thus, that could eventually lead to an incorrect computation of the general and simple propensity score and then bias the treatment effect estimation.

4 Data, variables and descriptive statistics

4.1 Data

We combine six different data sources on individual firms to build up our final data set. Our first data source comprises R&D data for the period 1993-2009 from the mandatory survey on R&D (Statistics Office - Ministry of Higher Education and Research) collected each year by the Direction of Evaluation, Prospective and Performance (DEPP). This so-called “R&D survey” inquires about the amount and the types of investments and expenditures related to R&D as defined in the Frascati Manual guidelines (OECD, 2002). It includes declarative data such as the amount of internal and external R&D investments as well as the different external funding coming either from public bodies or private firms. Public R&D funding includes civil and military R&D contracts as well as R&D subsidies granted by the different public administrative bodies in charge of R&D policies (e.g. Ministry of Research, Ministry of Industry) or other public agencies (e.g. Oséo-ANVAR, ADEME).

Our second data source is the R&D tax credit register from the Ministry of Higher Education and Research, which manages the French R&D tax scheme. The data are exhaustive and reveal the amount of R&D tax credit obtained by firms on a yearly basis. As a negative tax credit can be carried forward by firms, the net positive value of the annual tax credit is considered as the amount likely to positively affect the efforts of firms in R&D investments. Furthermore, since 1997 firms are supposed to consolidate their R&D declaration and R&D tax credit claims at the business group level. The R&D tax credit files allow us to identify fiscal groups: headquarters as well as the subsidiaries they are consolidated with.

The third data set is the annual business survey EAE (enquêtes annuelles d’entreprises) from 1993 to 2007. The survey managed by the French National Institute of Statistics and Economic Studies (INSEE) reports the individual characteristics of French manufacturing firms with more than 20 employees and service firms with more than 10 employees. It provides the main activity (NACE code), accounting data, some data

on workforce and investments. Among them the number of employees, value added, exports, cash flow and operating subsidies are variables of particular interest to us. Our fourth data set named ESANE (Elaboration des statistiques annuelles d'entreprise) is provided by the Ministry of Finance for 2008 and 2009 at the place of the annual business survey, which however is not available anymore. ESANE comprises different fiscal and administrative data coming from fiscal and social declarations. The file is not a survey and encompasses millions of firms compared to the EAE files. Most of the variables coming from the EAE survey can be retrieved in ESANE. Missing values are however more frequent especially for SMEs. We thus complete the ESANE data with our fifth source of information: a private database (DIANE) gathering the information disclosed to commercial courts by French firms and published by Bureau van Dijk. When data from ESANE are missing, we impute them by using DIANE values.

Our sixth data source is the 'financial linkages' data set (LIFI) that covers the period 1993-2009 and is provided by INSEE in collaboration with Bureau van Dijk. LIFI provides information upon headquarters for every subsidiary that is located in France and that is fully or owned (at least at 50%) by another firm. Thanks to LIFI, we are able to identify firms located in France owned by foreign companies.

5 Variables

Obviously, the treatment variable is the amount of the R&D subsidy received from the government or other public institutions.

Our matching techniques are based on the following pre-treatment variables: R&D intensity indicator (private R&D expenditure over value added), dummies for positive cash flow, exports scaled to sales, foreign ownership, dummies referring to the second and third distribution terciles of our treatment variables and other subsidy, 2-digit industry and size dummies. Specifically, size dummies are defined as follows: firms between 20 and 49, between 50 and 99, 100 and 499 and equal or larger than 500 employees. This classification finds justification in the French industrial structure that is dominated by SMEs: enterprises with less than 50 employees account for more than 95% of the total firm population (e.g. Garicano et al., 2013).

Several among these covariates typically appear also in the related literature. The industry and size dummies account for potential common demand/supply shocks or idiosyncratic shocks to a given company size or a given industry level, while the other pre-treatment variables capture unobservable or observable firm heterogeneity. The inclusion in the selection equations of the dummies indicating past public support accounts for firms' 'dependence'. The cash flow dummy proxies for firm financial constraints: if the policy maker prefers to support businesses with financial constraints, firms with a positive cash flow may result disadvantaged vis-a-vis firms with negative cash flow. The exports sales ratio and the variable indicating

the foreign ownership may reveal a policy maker’s inclination to fund companies more active in international markets, possibly characterized by higher productivity levels with larger potential for innovations.⁶ Thus, each variable in the selection equation expresses our attempt to account for all possible criteria that French public authorities may use for the targeting of their subsidies.

5.1 Descriptive startistics

Figure 1 shows the average annual public R&D subsidy and R&D tax credit for our sample of firms. Consistent with what stated in the section on the institutional background, we observe an increasing amount of public resources devoted to the R&D tax credit and a trend reduction in the provision of R&D subsidies over time. A notable discontinuity in the average R&D tax credit clearly emerges in 2004 and 2008 that are in fact the years of major reshaping of such a policy tool. Figure 2 adds a further information on the level of average private expenditure in R&D. In our sample, it increases from the early 90s to the year 2000 and decreases afterwards. In Figure 3, the average private R&D expenditure for both treated (with subsidy only) and untreated, and the average total public R&D financing to recipients are reported. It emerges that on average financed firms invest more in their research activities. Similarly, Figure 4 shows that firms benefiting from both R&D subsidies and R&D tax credit report higher values of their private R&D expenditure than non-recipients.

Table 1 describes the main variables used in the analysis, favoring the comparisons across three categories of firms. The first two variables listed are the treatment variables: R&D public subsidy and total R&D public support. Next, the two outcome variables (the dependent variables of our analysis) are the private R&D and % change of private R&D. The remaining listed variables are the covariates used to determine the matching between control and treated. Firms are divided into three groups: R&D subsidy recipients, R&D subsidy and R&D tax credit recipients and non-recipients. Although the latter group is a residual category, it however includes R&D performing firms. The control group counts 14,056 companies, whereas treated groups consist of 4,279 enterprises funded with R&D subsidies and 3,173 firms supported with both R&D subsidies and R&D tax credit. Although most of the pre-treatment variables are quite similar when we compare R&D subsidy recipients with R&D subsidy and R&D tax credit recipients, it is worth noting that the R&D intensity is much higher for enterprises financed with both policy tools whereas firms receiving only R&D subsidy report a R&D value added ratio just slightly higher than non-funded firms. In addition, current recipients firms have more likely benefited from public support schemes in the previous periods. Comparing average outcome variables among firm groups, we observe that the highest level of private R&D expenditure is associated with recipients of both R&D subsidy and R&D tax credit, followed by subsidy-only recipients

⁶Bernard and Jensen (1999) and Melitz (2003) among others.

and by non-recipients. However, this ranking changes drastically if we consider the average % change in private R&D expenditure: non-recipients seem to outperform recipient groups, and subsidy-only recipients perform better than fully supported firms.

Table 2 and Table 3 present a similar structure to the previous table and facilitate the comparisons between different groups of firms: funded firms are divided into three groups corresponding to the first, second and third tercile of the public subsidy distribution, respectively. It turns out that whereas the average private R&D expenditure increases with the tercile of public R&D provision, the opposite pattern emerges when considering the % change in private R&D expenditure as outcome variable. This, combined with the similar statistics reported in Table 1, represents an interesting *prima facie* evidence that, if confirmed in our causal analysis, may cast serious concerns on the targeting and effectiveness of public resources devoted to propel private R&D investment.

6 Results

This section presents the results based on our categorical and continuous matching evaluation schemes. In the first approach, we divide financed firms into three categories reflecting the terciles of the distribution of the R&D support grant as well as the terciles of the distribution of the R&D subsidy and R&D tax credit. This choice is clearly data-driven since it is not grounded on any a priori knowledge about optimal amount thresholds. Although the decision of partitioning the entire distribution of our treatment variables in three equally populated groups is to some extent arbitrary, it appears to us as the most sensible option given the size of our sample. In fact, we face the trade-off between the number of groups analyzed with the observations available in each group. If the observations is not sufficient, not only estimates lose efficiency, but the estimation method also becomes unfeasible due to the lack of a common support. This limit may not affect the continuous matching method, because it approximates the distribution of public funds according to a normal density function.

6.1 Main results

Table 4 and 5 summarize the estimates obtained by means of the categorical matching method for our outcome variables, namely the log-level and the log-difference (i.e. growth rate) of private R&D spending. Whereas the former variable eases the interpretation of our treatment effect, the latter better accounts for time-invariant unobserved heterogeneity and therefore constitutes our benchmark when evaluating the average treatment on treated (ATT) estimates.

The first three columns of Table 4 are related to R&D subsidy-only recipients. The first column refers

to the standard dichotomous matching method in which all categories of publicly financed firms (*small*, *medium* and *large* R&D subsidy-only recipients) are compared with untreated ones (non-recipients). This simple comparison shows a quite large positive and significant effect of public subsidy provision: on average the set of financed firms invests about 12% more than not financed ones. However, scrutinizing the pairs of differently funded versus unfunded companies, this result is not confirmed for the first and for the second tercile. In this case, the treatment effect is positive but insignificant. Whereas *small* grant and *medium* grant recipient firms do not outperform untreated ones, *large* grant recipients invest significantly more in private R&D than non recipients. This underlines the importance of splitting the treatment evaluation in our three categories. Interestingly, the input additionality emerges extensively in all other comparisons between more and less treated firms (column 2 and 3). More precisely, *medium* grant recipients spend on average about 2.2 times more than *small* ones, and *large* grant recipients invest about 2.6 and 1.4 times more than *small* and *medium* grant recipients, respectively. However, these findings are not in line with effects of the public R&D subsidy provision in combination with the R&D tax credit support, which are shown in columns 4, 5 and 6 of Table 4. No significant ATTs are reported, except for the *medium* grant recipients that seem to spend twice more in private R&D compared to non-recipients.

Mostly insignificant results are reported also in Table 5, where ATTs are differences in the growth rates of private R&D expenditure between firm groups. Furthermore, we find strong crowding-out evidence when (i) comparing *large* with *small* R&D subsidy recipients under R&D tax credit benefits (-1.4%), and (ii) confronting *large* R&D grant recipients with non-recipients in absence (-1%) or in combination of R&D tax credit benefits (-1.9%). This clearly indicates that companies receiving the largest doses of treatment may substitute private R&D expenditure with public R&D subsidies. In line with this argument, we deepen our analysis to investigate the role that different amounts of public R&D subsidies may have in determining an additionality or crowding-out effect of public R&D financing by performing a propensity score matching by year.

To this purpose, findings on the effectiveness of R&D public subsidy in absence or combination with R&D tax credit is respectively illustrated in Figure 5-14 and Figure 15-24. In these figures we plot the average log-level of private R&D expenditure and the average difference in % change of the average log-level of private R&D expenditure, so vertical differences represent the treatment effects (ATTs). The presence of dots reveals that the computed ATT for a given year is statistically significant at 5 percent level. The use of such graphs facilitates the comparison of ATTs over time and allows for an evaluation of the effects induced by sharp changes (discontinuities) in the provision of R&D public support, i.e. first difference in ATT. However, if on the one hand the assignment of propensity scores by year improves the adequacy of matched pairs, on the other hand a more demanding method reduces the number of matched firms and therefore enlarges the

estimated standard errors.

Looking at graphs for which the outcome variable is the log-level of private R&D expenditure, we find that *large* grant recipients outperform untreated or less treated firm groups mostly before the 2004 reform, and significant crowding-out effects emerge in a few cases when comparing *medium* and *small* categories with non-recipient firms. Instead, when we turn our attention on the % change of private R&D expenditure, only in some cases treated firms perform better than untreated ones, with significant coefficients typically reported for the years 1998 and 1999. Moreover, proceeding with our inter-tercile comparisons, figures display no significant ATTs over the sample period. The overall picture seems not to change after the analysis of figures reporting the impact of subsidy under tax credit on both outcome variables. Again, *small* and *medium* subsidy recipients under tax credit underperform or do not perform better than firms not receiving any R&D public aids when taking the outcome variable in log-levels or % changes, respectively. In average terms, recipients of *large* subsidy under tax credit present higher average level of private R&D expenditures than *medium* and *small* subsidy recipients, which are however significant only for the years 2000, 2001 and 2002. Mostly insignificant effects are reported for the inter-tercile comparisons on % changes of private R&D expenditure.

As stated above, we complement these results from the inter-tercile (i.e. categorical treatment) evaluation with those from the intra-tercile (i.e. continuous treatment) comparisons to add further information aimed at the overall assessment of the R&D policy. As mentioned in the methodological section, the continuous treatment matching method allows for the comparison of responses given small increases in the treatment doses. It implies that non-recipients are not included in such an evaluation because their dose is zero (they are untreated). Figure 25-28, which refer to this method, report the dose response function: the outcome (response) variable is on the y-axis and the treatment (dose) on the x-axis. Thus, the slope of the dose-response function indicates the effect associated with each amount of treatment. Obviously, if the slope of the dose-response function is decreasing (increasing) then the treatment effect is negative (positive): a marginal increase in the dose of treatment leads to a reduction (raise) of the private R&D expenditure.

When considering our outcome variable in log-levels (Figures 25 and 27), we find additionality effects for doses between 20,000 and 55,000 Euros (3 and 4 in log) and higher than 400 thousands Euros (6 in log). Treatment effect show that strong additionality arises just for amounts of subsidy within the third tercile, whereas smaller doses of treatment induce firms to marginally decrease their level of R&D investments. However, these findings are not confirmed in the analysis on the % change in private R&D spending, which provide evidence of crowding-out or no effects of public R&D provision both with or without the interaction with the R&D tax credit. It turns out that higher substitution of private with public R&D resources is more likely among *large* doses (above 400 thousands Euro) recipients. Since differences in % changes do better

account for firm specific time-invariant effects, we are more confident in evaluations having such an outcome variable.

We re-run all comparisons done in the propensity score categorical matching analysis by using the exact matching evaluation approach. The main difference between these two methods is that in latter version we fix an exact matching among a number of pre-treatment covariates: size, industry, (R&D tax credit, R&D subsidy and other subsidy) recipient status, exporter status, and foreign ownership dummies. We report in Figure 29-33 (34-38) the effects of R&D subsidy in absence (combination with) R&D tax credit. Overall, the exact matching evaluation corroborates the pscore findings.

7 Conclusions

A general recognition that innovation-driven economic success can be influenced by ad-hoc policy interventions has become a key point in the policy agendas across many countries. The rationale that government interventions supporting private R&D are seen as necessary in the market economy has determined a shift in the current debate, which is primarily focused on designing a successful technology “policy mix” for boosting innovation. This implies that policy evaluators should attempt at incorporating considerations on interdependencies and influences of other R&D policy tools when assessing the extent to which a given R&D policy tool has produced the desired policy outcomes.

This paper discusses precisely the importance of this aspect in the evaluation of the public subsidies to R&D, proposing an assessment of this policy under the regime of the R&D tax credit, equally important policy instrument often used as complement of the direct R&D funding. In addition, the present article introduces an intra-group assessment of the outcome of these policies. Unlike an inter-group analysis directed to investigate a differentiated impact of R&D grants across differently funded firms, an intra-group analysis investigates the implications of the current modulation of public intervention for similarly funded firms. Implemented by means of a continuous treatment evaluation method, it allows us to investigate the likelihood of crowding-in and crowding-out effects within each tercile along the distribution of the public R&D support grant. The inter-tercile comparison is also presented aside using the categorical matching method. Both methods are coupled with the DiD approach to account for unobserved heterogeneity and result strengthened by a rich data set featuring comprehensive information on the pre-treatment variables.

Our results show that a notable substitution between private and public funds occurs, especially for high level of the public subsidy. Recipients of larger doses do not outperform recipients of lower doses or even non-recipient firms. The substitution becomes more apparent when we analyze the intra-tercile distribution of public funds under tax credit: we highlight a considerable reduction in growth of private R&D expenditure

among the top beneficiary companies. Specifically, it emerges - on average - that funded firms receiving subsidies up to 400 thousands Euros exhibit a low private contribution with respect to their counterfactual units. Overall these results indicate that an ex-post evaluation of the targets of a R&D policy is desirable, if not necessary in time of downturns. In fact, if R&D funding has to become a valid policy instrument to support companies hardly hit by a crisis and facing financial restrictions, it is inevitable that public resources should not be re-directed away from risky and promising long-term research projects toward the big players who would perform equally well without these funding.

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Table 1: Descriptive Statistics: Recipients vs Non Recipients

Variable	<i>Subsidy Recipients</i>			<i>Subsidy and Tax Credit Recipients</i>			<i>Non Recipients</i>		
	mean	st.dev.	N	mean	st.dev.	N	mean	st.dev.	N
<i>Treatment variables</i>									
subsidy	3,976.898	26,165.516	4,279	4,015.581	24,776.99	3,173	0	0	14,056
tax credit	0	0	4,279	1,406.929	4,487.35	3,173	0	0	14,056
<i>Outcome variables</i>									
private R&D	19,123.567	91,684.81	4,279	23,201.275	92,956.012	3,173	3,665.654	17,899.276	14,056
% change private R&D	1.278	2.687	4,279	0.831	2.624	3,173	1.673	2.734	14,056
<i>Pre-treatment variables</i>									
subsidy_2nd	0.165	0.371	4,279	0.169	0.375	3,173	0.024	0.153	14,056
subsidy_3rd	0.288	0.453	4,279	0.284	0.451	3,173	0.014	0.118	14,056
tax credit_2nd	0.049	0.217	4,279	0.167	0.373	3,173	0.056	0.23	14,056
tax credit_3rd	0.156	0.363	4,279	0.484	0.500	3,173	0.097	0.296	14,056
other subsidy_2nd	0.104	0.305	4,279	0.108	0.311	3,173	0.145	0.352	14,056
other subsidy_3rd	0.616	0.486	4,279	0.579	0.494	3,173	0.343	0.475	14,056
cash	0.812	0.390	4,279	0.808	0.394	3,173	0.837	0.369	14,056
R&D VA ratio	0.070	8.175	4,279	0.447	8.067	3,173	0.053	3.897	14,056
export intensity	0.336	0.285	4,279	0.375	0.296	3,173	0.317	0.278	14,056
foreign ownership	0.276	0.447	4,279	0.284	0.451	3,173	0.454	0.498	14,056
size(20-50)	0.143	0.35	4,279	0.135	0.341	3,173	0.127	0.333	14,056
size(50-100)	0.156	0.363	4,279	0.148	0.356	3,173	0.147	0.354	14,056
size(100-500)	0.365	0.482	4,279	0.349	0.477	3,173	0.475	0.499	14,056
size(>500)	0.318	0.466	4,279	0.350	0.477	3,173	0.234	0.423	14,056

Notes: Monetary values are reported in thousands of euros and deflated at 2000 year price level.

Table 2: Descriptive Statistics: Terciles of Subsidy Recipients

Variable	<i>1st Tercile</i>			<i>2nd Tercile</i>			<i>3rd Tercile</i>		
	mean	st.dev.	N	mean	st.dev.	N	mean	st.dev.	N
<i>Treatment variables</i>									
subsidy	15.723	8.481	1,336	79.608	41.21	1,353	10,621.655	42,105.88	1,590
tax credit	0	0	1,336	0	0	1,353	0	0	1,590
<i>Outcome variables</i>									
private R&D	3,322.397	11,756.43	1,336	5,302.649	16,262.052	1,353	44,161.345	145,912.389	1,590
% change private R&D	1.696	2.617	1,336	1.409	2.62	1,353	0.816	2.733	1,590
<i>Pre-treatment variables</i>									
subsidy_2nd	0.124	0.33	1,336	0.282	0.45	1,353	0.098	0.298	1,590
subsidy_3rd	0.038	0.192	1,336	0.128	0.334	1,353	0.625	0.484	1,590
tax credit_2nd	0.064	0.244	1,336	0.062	0.241	1,353	0.03	0.169	1,590
tax credit_3rd	0.138	0.345	1,336	0.131	0.337	1,353	0.189	0.391	1,590
other subsidy_2nd	0.142	0.349	1,336	0.105	0.307	1,353	0.064	0.245	1,590
other subsidy_3rd	0.513	0.5	1,336	0.523	0.5	1,353	0.672	0.47	1,590
cashl	0.871	0.335	1,336	0.824	0.381	1,353	0.753	0.432	1,590
R&D VA ratio	0.065	0.767	1,336	0.151	0.641	1,353	0.007	13.383	1,590
export intensity	0.321	0.279	1,336	0.325	0.281	1,353	0.358	0.292	1,590
foreign ownership	0.322	0.467	1,336	0.273	0.446	1,353	0.242	0.428	1,590
size(20-50)	0.192	0.394	1,336	0.163	0.369	1,353	0.084	0.278	1,590
size(50-100)	0.18	0.385	1,336	0.17	0.376	1,353	0.124	0.33	1,590
size(100-500)	0.386	0.487	1,336	0.407	0.491	1,353	0.313	0.464	1,590
size(>500)	0.223	0.416	1,336	0.246	0.431	1,353	0.46	0.499	1,590

Notes: Monetary values are reported in thousands of euros and deflated at 2000 year price level.

Table 3: Descriptive Statistics: Terciles of Subsidy and Tax Credit Recipients

Variable	<i>1st Tercile</i>			<i>2nd Tercile</i>			<i>3rd Tercile</i>		
	mean	st.dev.	N	mean	st.dev.	N	mean	st.dev.	N
<i>Treatment variables</i>									
subsidy	17.609	9.936	1,046	89.226	41.725	980	11,016.198	40,278.769	1,147
tax credit	398.762	1028.291	1,046	613.098	1946.32	980	3,004.573	6,892.999	1,147
<i>Outcome variables</i>									
private R&D	4,226.786	14,115.036	1,046	8,202.227	48,058.894	980	53,320.177	142,594.274	1,147
% change private R&D	1.235	2.519	1,046	0.873	2.53	980	0.427	2.737	1,147
<i>Pre-treatment variables</i>									
subsidy_2nd	0.134	0.341	1,046	0.287	0.452	980	0.1	0.3	1,147
subsidy_3rd	0.045	0.207	1,046	0.133	0.339	980	0.63	0.483	1,147
tax credit_2nd	0.211	0.408	1,046	0.217	0.413	980	0.083	0.276	1,147
tax credit_3rd	0.364	0.481	1,046	0.431	0.495	980	0.638	0.481	1,147
other subsidy_2nd	0.163	0.369	1,046	0.112	0.316	980	0.056	0.23	1,147
other subsidy_3rd	0.493	0.5	1,046	0.546	0.498	980	0.686	0.464	1,147
cashl	0.859	0.348	1,046	0.817	0.387	980	0.754	0.431	1,147
R&D VA ratio	0.537	13.574	1,046	0.198	0.687	980	0.577	3.411	1,147
export intensity	0.347	0.296	1,046	0.352	0.288	980	0.419	0.298	1,147
foreign ownership	0.312	0.463	1,046	0.281	0.45	980	0.262	0.44	1,147
size(20-50)	0.167	0.373	1,046	0.172	0.378	980	0.074	0.262	1,147
size(50-100)	0.178	0.383	1,046	0.168	0.374	980	0.105	0.306	1,147
size(100-500)	0.394	0.489	1,046	0.387	0.487	980	0.276	0.447	1,147
size(500)	0.238	0.426	1,046	0.253	0.435	980	0.534	0.499	1,147

Notes: Monetary values are reported in thousands of euros and deflated at 2000 year price level.

Table 4: Pscore Matching: ATT Estimates (differences in log-levels of private R&D)

	<i>Subsidy</i>			<i>Subsidy and Tax Credit</i>		
	Non Recipients	Small	Medium	Non Recipients	Small	Medium
Recipients	0.1166** (0.0578)			-0.0301 (0.0844)		
Small	0.0249 (0.7131)			-0.2091 (0.8544)		
Medium	0.0387 (0.6897)	2.1856*** (0.7987)		2.1369** (0.9674)	-0.2638 (0.9939)	
Large	0.9221* (0.5430)	2.5523*** (0.6264)	1.3490** (0.6687)	0.7419 (0.7972)	0.3943 (0.7871)	0.5684 (0.9921)

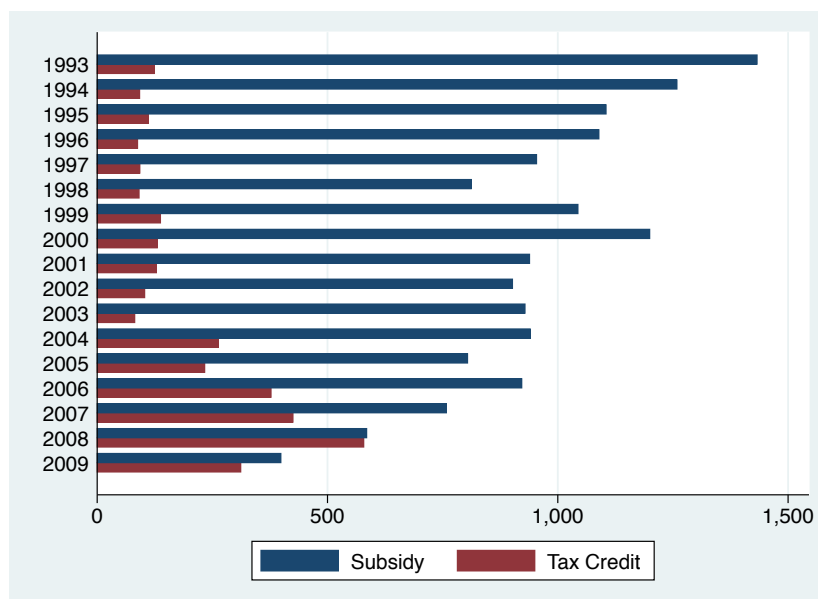
Notes: We hereby report the Average Treatment on Treated. The caliper is set equal to 0.01. Significance levels: ***(1%),**(5%), *(10%).

Table 5: Pscore Matching: ATT Estimates (differences in % changes of private R&D)

	<i>Subsidy</i>			<i>Subsidy and Tax Credit</i>		
	Non Recipients	Small	Medium	Non Recipients	Small	Medium
Recipients	0.0627 (0.0858)			-0.0588 (0.1055)		
Small	-1.0195 (0.9347)			-1.3112 (0.8502)		
Medium	-1.2024 (0.8912)	0.9078 (0.9486)		0.5206 (0.9439)	0.5646 (0.9711)	
Large	-1.0547* (0.5934)	0.4436 (0.6259)	0.3511 (0.5983)	-1.9069*** (0.6426)	-1.3638* (0.7793)	0.1203 (0.6606)

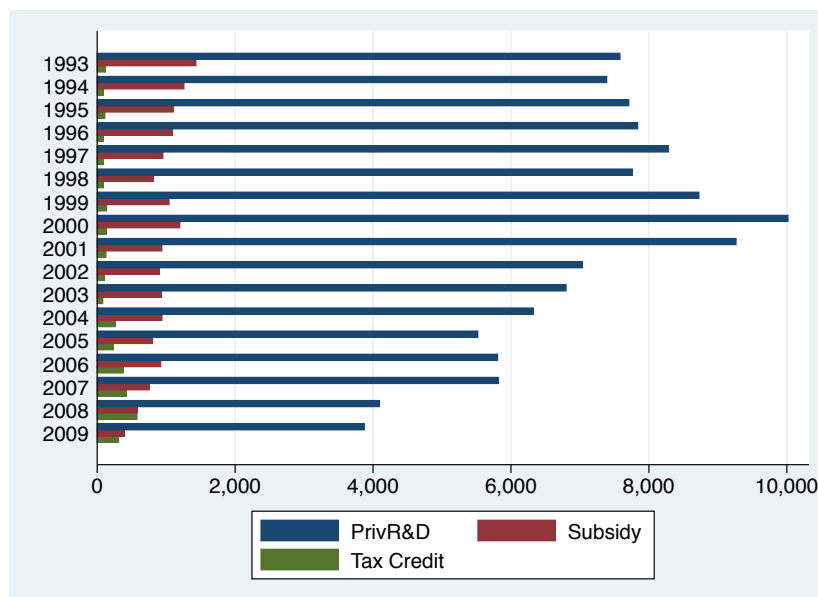
Notes: We hereby report the Average Treatment on Treated. The caliper is set equal to 0.01. Significance levels: ***(1%),**(5%), *(10%).

Figure 1: Average Public Funding and Tax Credit



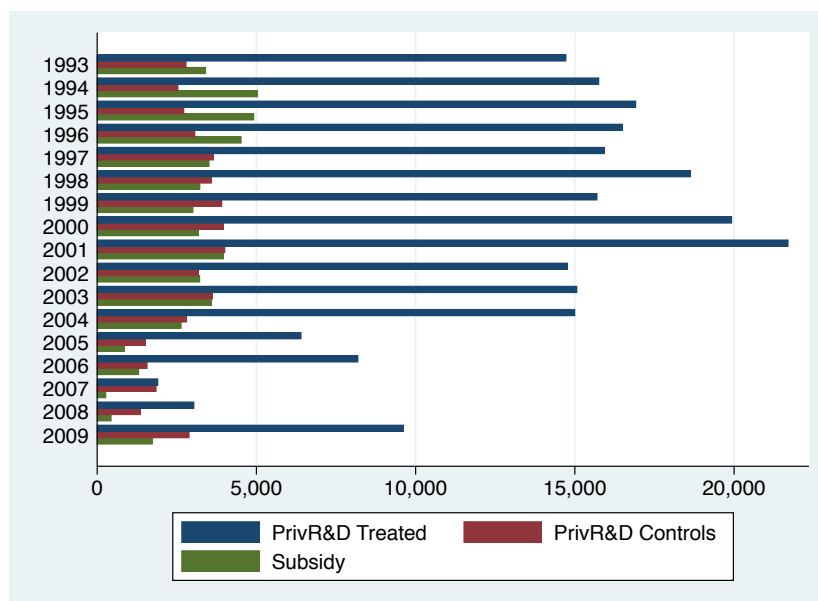
Notes: All values are reported in thousands of euros and deflated at 2000 year price level.

Figure 2: Average Private R&D Expenditure (PrivR&D), Public Funding and Tax Credit



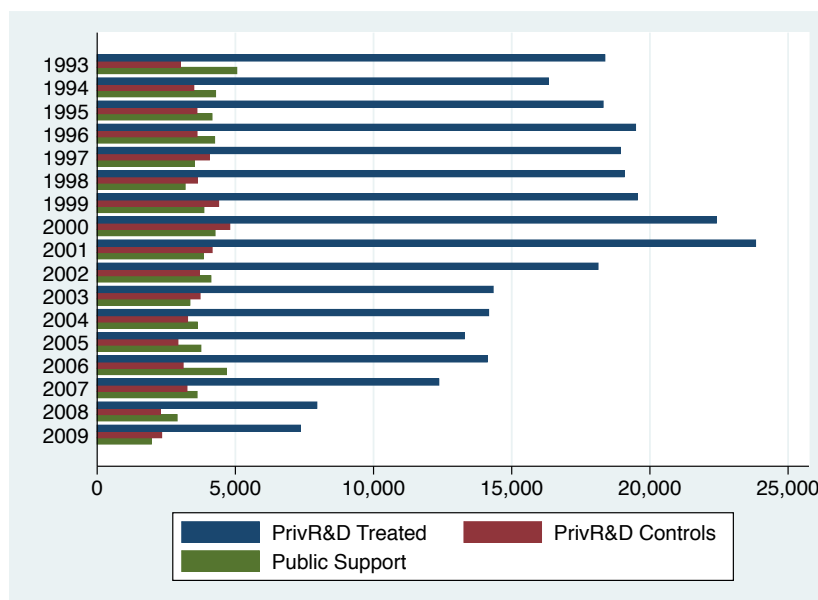
Notes: All values are reported in thousands of euros and deflated at 2000 year price level.

Figure 3: Average Private R&D Expenditure of Treated and Controls, and Subsidy



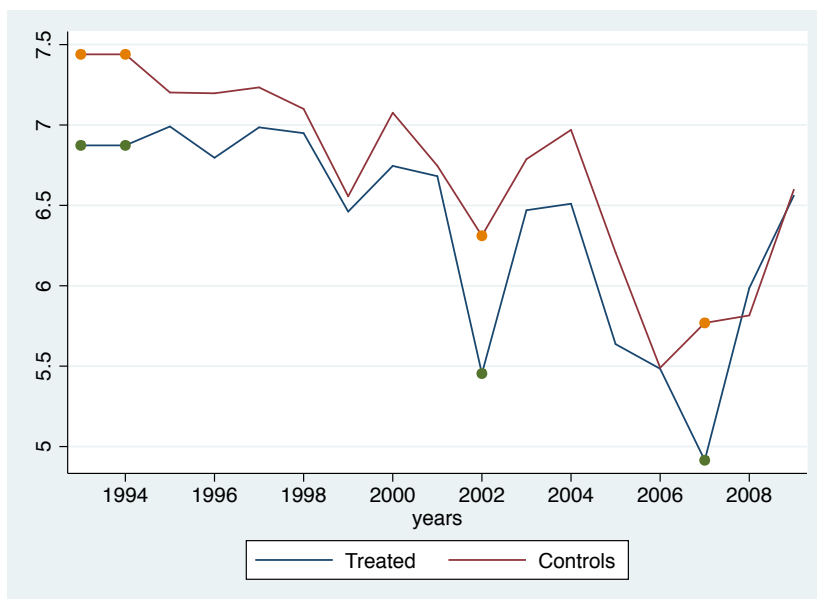
Notes: All values are reported in thousands of euros and deflated at 2000 year price level.

Figure 4: Average Private R&D Expenditure of Treated and Controls, and Public Support (Public Funding+Tax Credit)



Notes: All values are reported in thousands of euros and deflated at 2000 year price level.

Figure 5: Pscore Matching: ATT Estimates - Differences in log-levels of Private R&D - Treated (Small) vs Controls - Subsidy



Notes: Dots indicate values for treated and controls whose differences are significant at 5% level.

Figure 6: Pscore Matching: ATT Estimates - Differences in log-levels of Private R&D - Treated (Medium) vs Controls - Subsidy



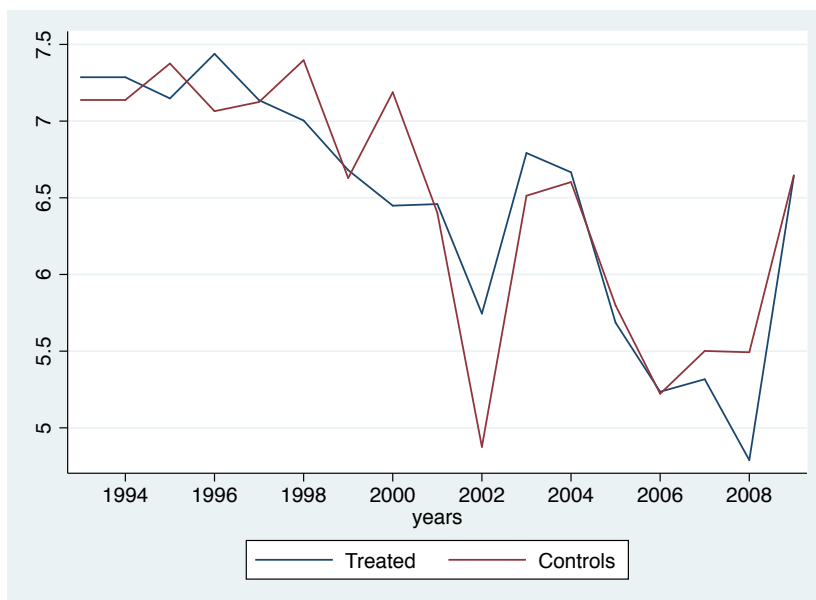
Notes: Dots indicate values for treated and controls whose differences are significant at 5% level.

Figure 7: Pscore Matching: ATT Estimates - Differences in log-levels of Private R&D - Treated (Large) vs Controls - Subsidy



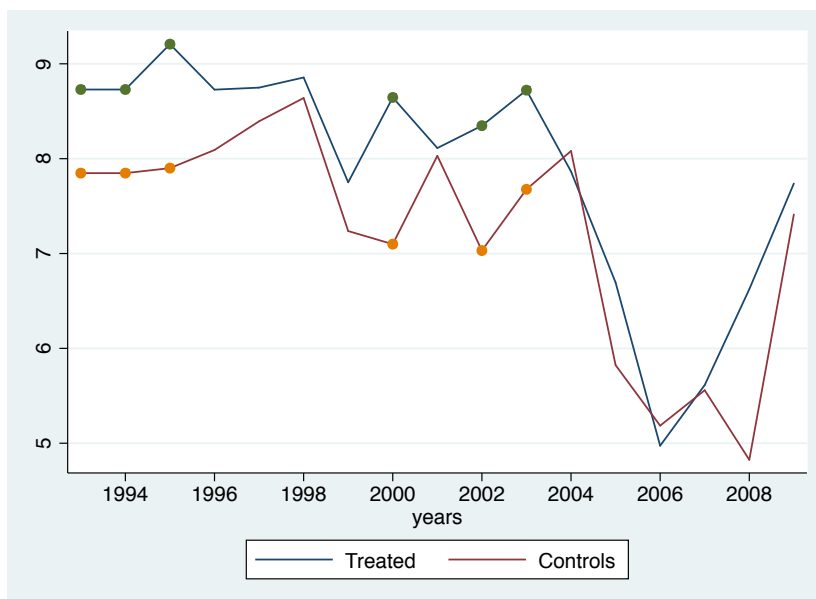
Notes: Dots indicate values for treated and controls whose differences are significant at 5% level.

Figure 8: Pscore Matching: ATT Estimates - Differences in log-levels of Private R&D - Treated (Medium) vs Controls (Small) - Subsidy



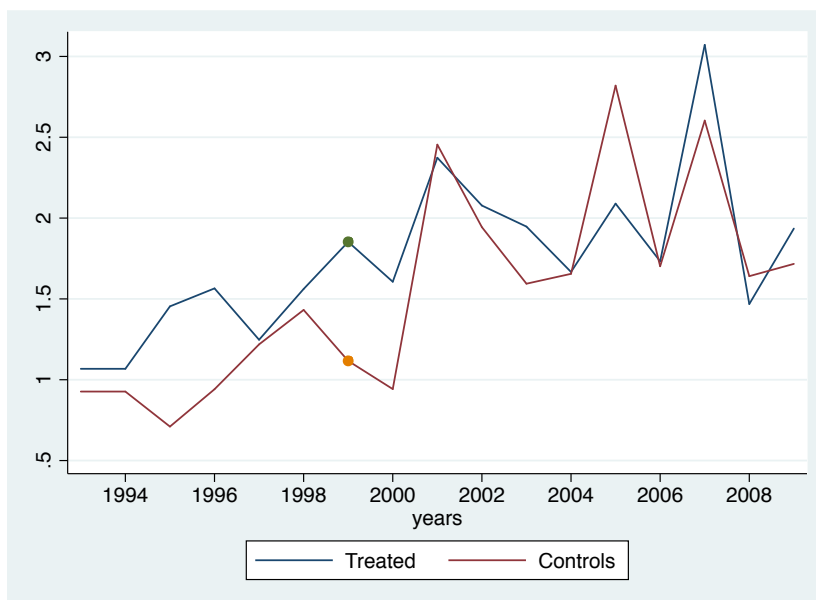
Notes: Dots indicate values for treated and controls whose differences are significant at 5% level.

Figure 9: Pscore Matching: ATT Estimates - Differences in log-levels of Private R&D - Treated (Large) vs Controls (Medium) - Subsidy



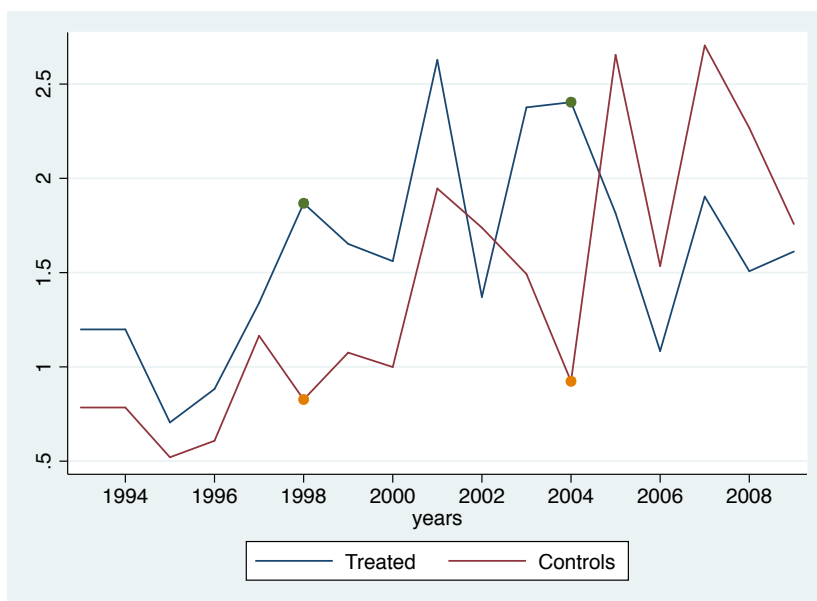
Notes: Dots indicate values for treated and controls whose differences are significant at 5% level.

Figure 10: Pscore Matching: ATT Estimates - Differences in % changes of Private R&D - Treated (Small) vs Controls - Subsidy



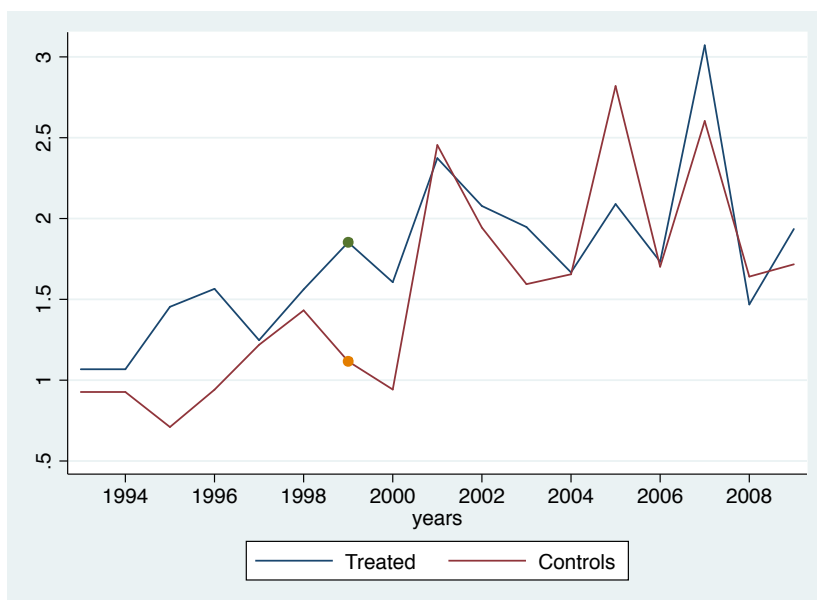
Notes: Dots indicate values for treated and controls whose differences are significant at 5% level.

Figure 11: Pscore Matching: ATT Estimates - Differences in % changes of Private R&D - Treated (Medium) vs Controls - Subsidy



Notes: Dots indicate values for treated and controls whose differences are significant at 5% level.

Figure 12: Pscore Matching: ATT Estimates - Differences in % changes of Private R&D - Treated (Large) vs Controls - Subsidy



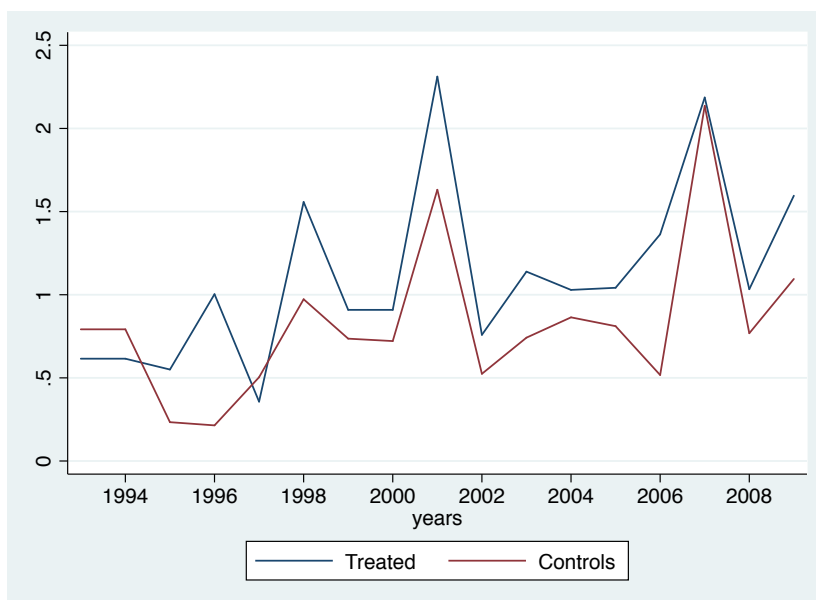
Notes: Dots indicate values for treated and controls whose differences are significant at 5% level.

Figure 13: Pscore Matching: ATT Estimates - Differences in % changes of Private R&D - Treated (Medium) vs Controls (Small) - Subsidy



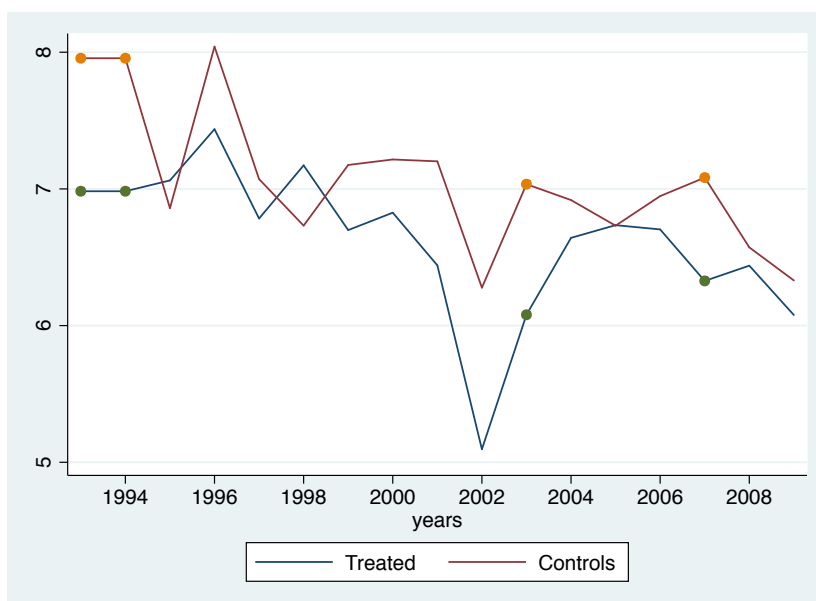
Notes: Dots indicate values for treated and controls whose differences are significant at 5% level.

Figure 14: Pscore Matching: ATT Estimates - Differences in % changes of Private R&D - Treated (Large) vs Controls (Medium) - Subsidy



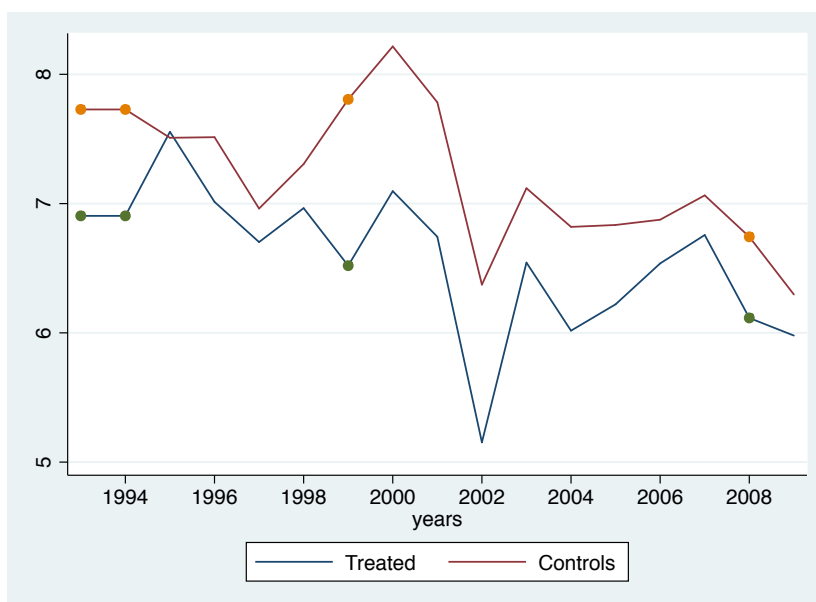
Notes: Dots indicate values for treated and controls whose differences are significant at 5% level.

Figure 15: Pscore Matching: ATT Estimates - Differences in log-levels of Private R&D - Treated (Small) vs Controls - Subsidy under Tax Credit



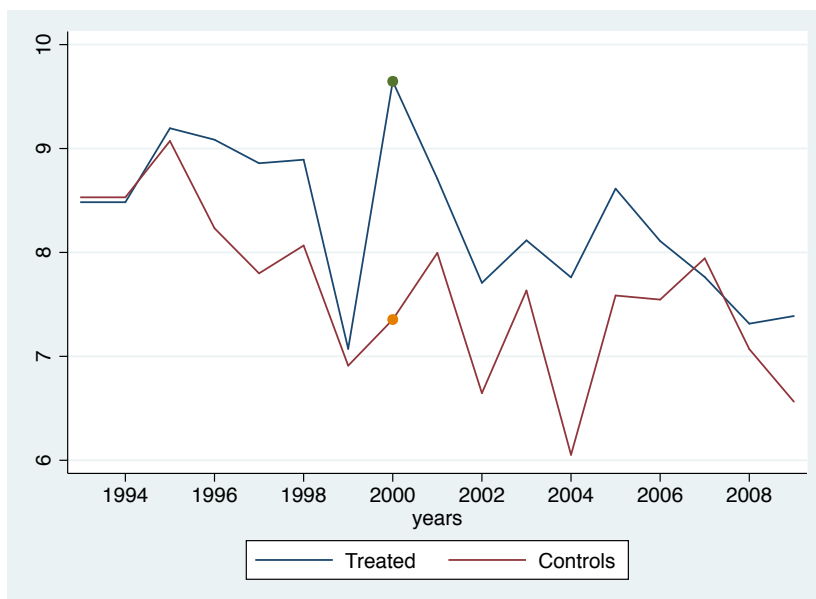
Notes: Dots indicate values for treated and controls whose differences are significant at 5% level.

Figure 16: Pscore Matching: ATT Estimates - Differences in log-levels of Private R&D - Treated (Medium) vs Controls - Subsidy under Tax Credit



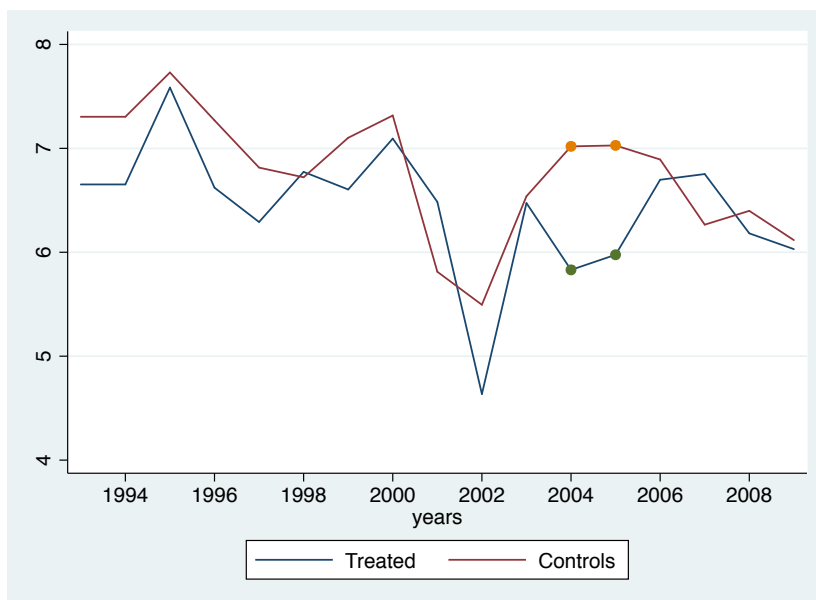
Notes: Dots indicate values for treated and controls whose differences are significant at 5% level.

Figure 17: Pscore Matching: ATT Estimates - Differences in log-levels of Private R&D - Treated (Large) vs Controls - Subsidy under Tax Credit



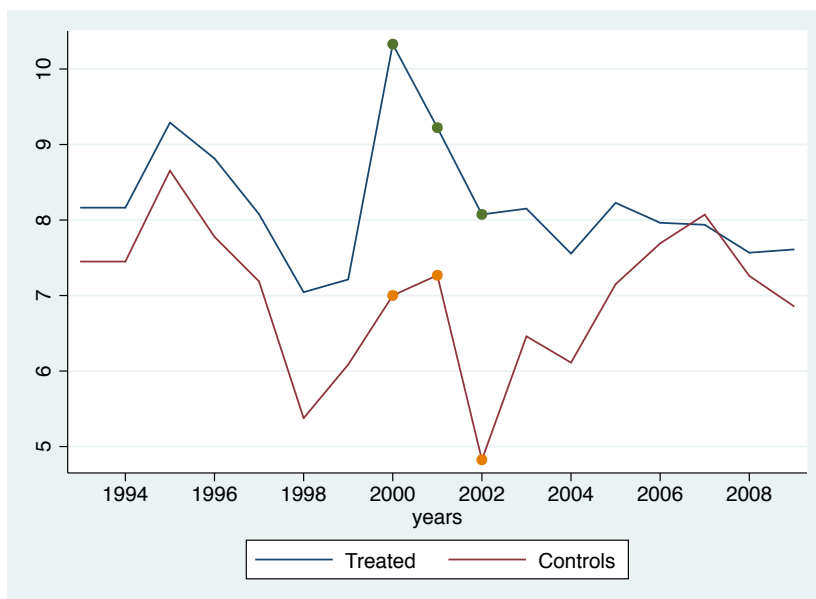
Notes: Dots indicate values for treated and controls whose differences are significant at 5% level.

Figure 18: Pscore Matching: ATT Estimates - Differences in log-levels of Private R&D - Treated (Medium) vs Controls (Small) - Subsidy under Tax Credit



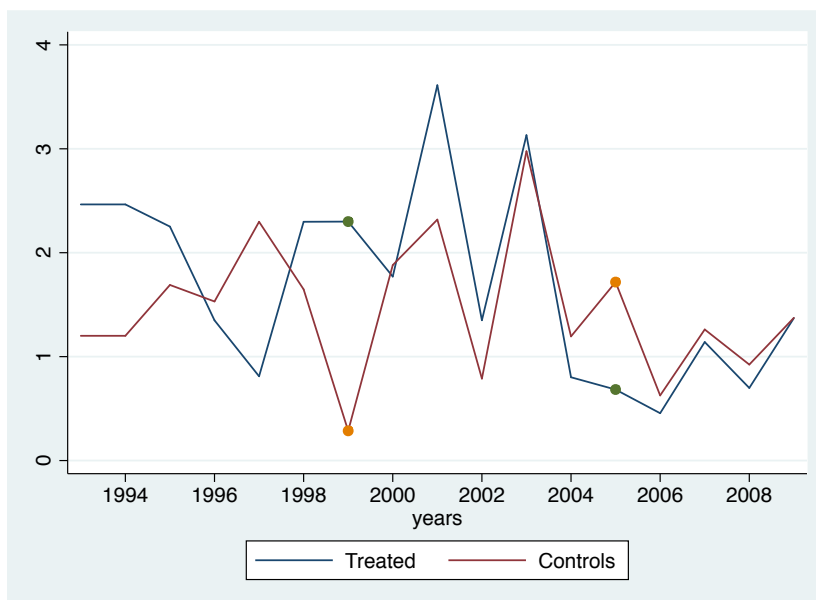
Notes: Dots indicate values for treated and controls whose differences are significant at 5% level.

Figure 19: Pscore Matching: ATT Estimates - Differences in log-levels of Private R&D - Treated (Large) vs Controls (Medium) - Subsidy under Tax Credit



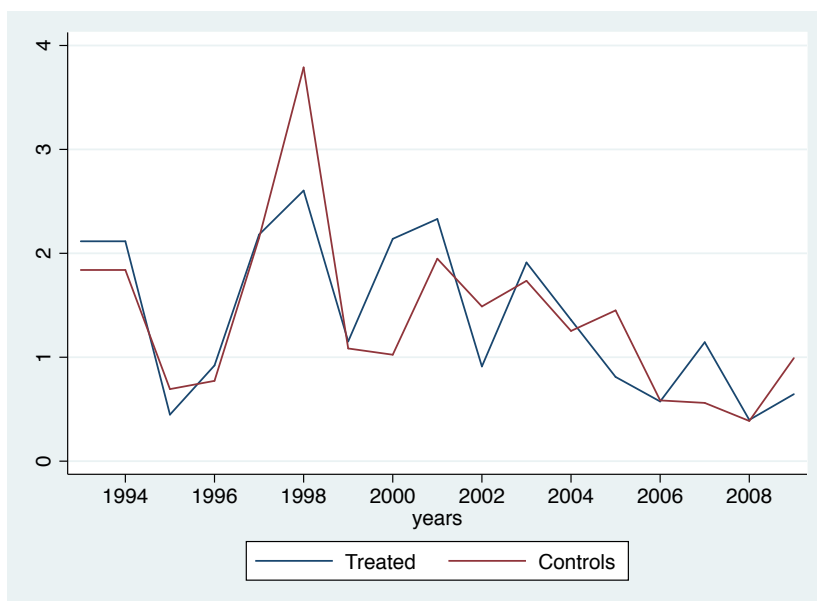
Notes: Dots indicate values for treated and controls whose differences are significant at 5% level.

Figure 20: Pscore Matching: ATT Estimates - Differences in % changes of Private R&D - Treated (Small) vs Controls - Subsidy under Tax Credit



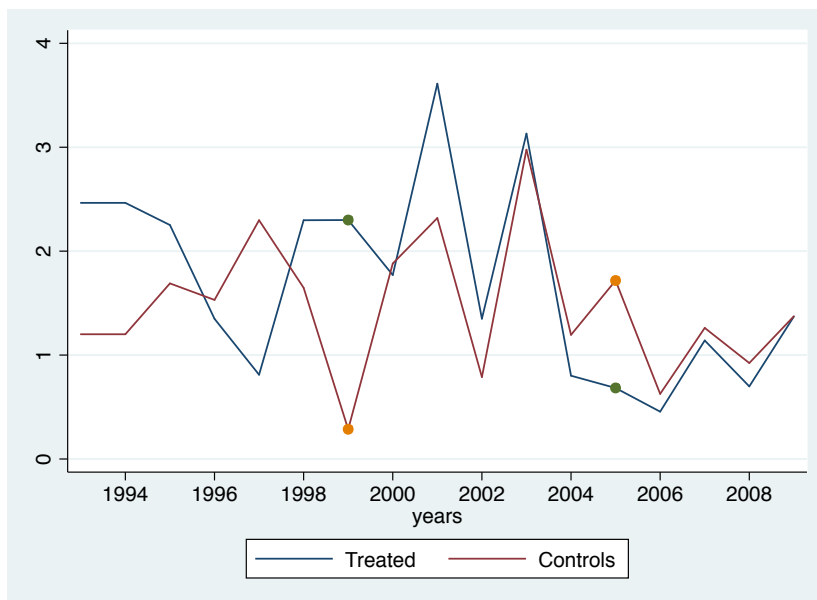
Notes: Dots indicate values for treated and controls whose differences are significant at 5% level.

Figure 21: Pscore Matching: ATT Estimates - Differences in % changes of Private R&D - Treated (Medium) vs Controls - Subsidy under Tax Credit



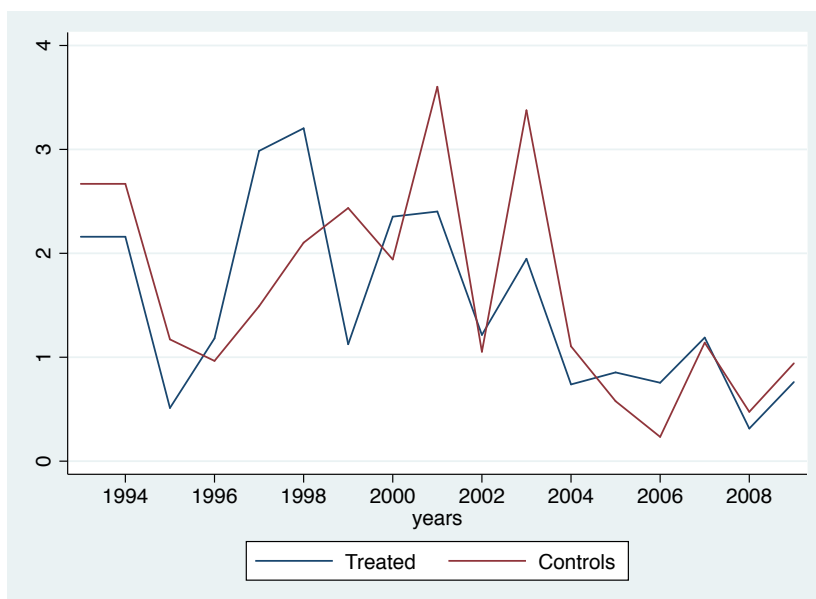
Notes: Dots indicate values for treated and controls whose differences are significant at 5% level.

Figure 22: Pscore Matching: ATT Estimates - Differences in % changes of Private R&D - Treated (Large) vs Controls - Subsidy under Tax Credit



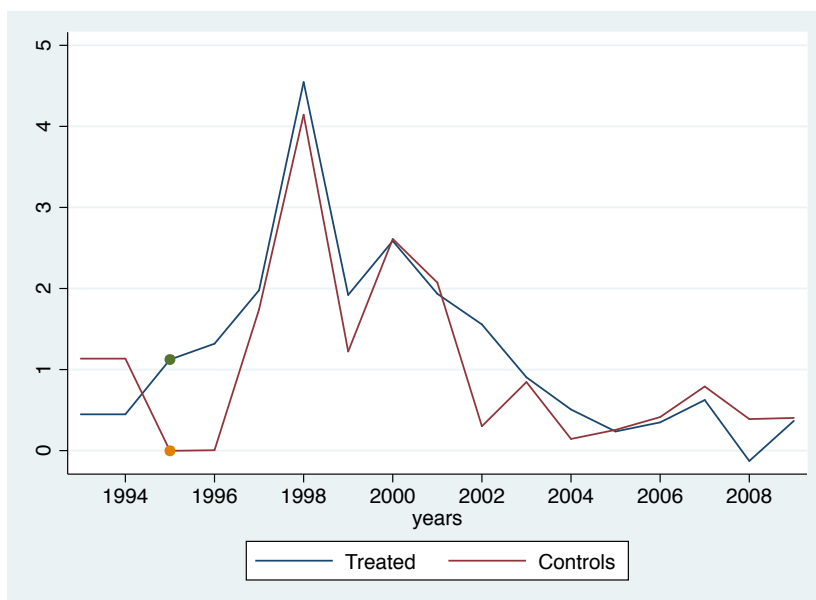
Notes: Dots indicate values for treated and controls whose differences are significant at 5% level.

Figure 23: Pscore Matching: ATT Estimates - Differences in % changes of Private R&D - Treated (Medium) vs Controls (Small) - Subsidy under Tax Credit



Notes: Dots indicate values for treated and controls whose differences are significant at 5% level.

Figure 24: Pscore Matching: ATT Estimates - Differences in % changes of Private R&D - Treated (Large) vs Controls (Medium) - Subsidy under Tax Credit



Notes: Dots indicate values for treated and controls whose differences are significant at 5% level.

Figure 25: Continuous Treatment Matching: Dose-Response and Treatment Effect - Differences in log-levels of Private R&D - Subsidy

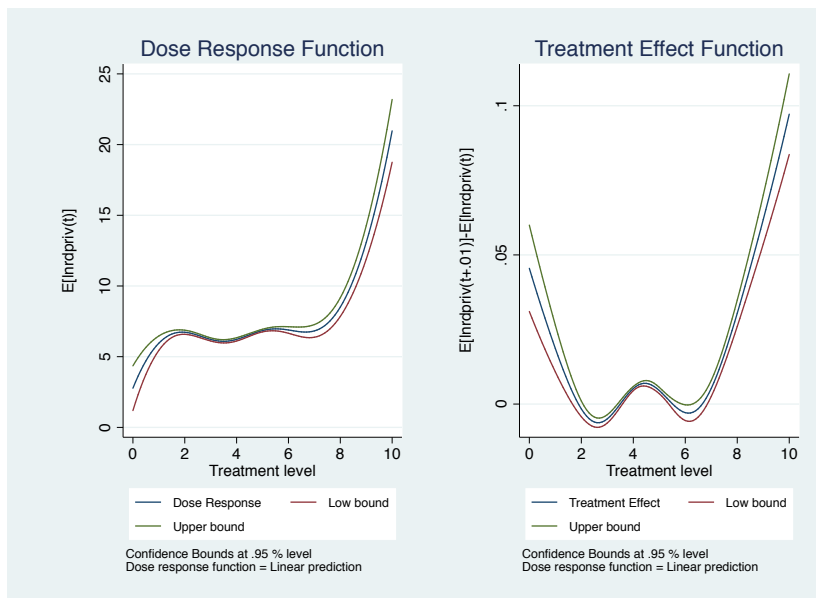


Figure 26: Continuous Treatment Matching: Dose-Response and Treatment Effect - Differences in % changes of Private R&D - Subsidy

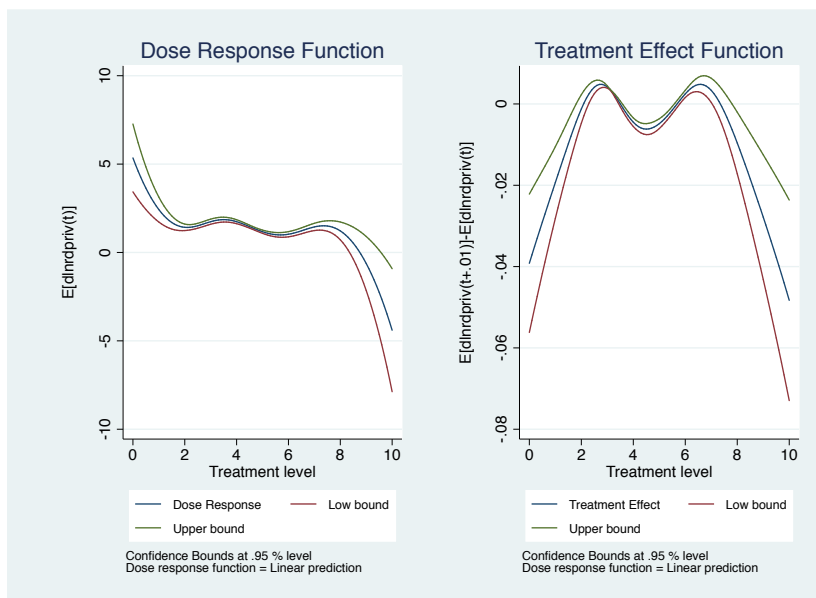


Figure 27: Continuous Treatment Matching: Dose-Response and Treatment Effect - Differences in log-levels of Private R&D - Subsidy under Tax Credit

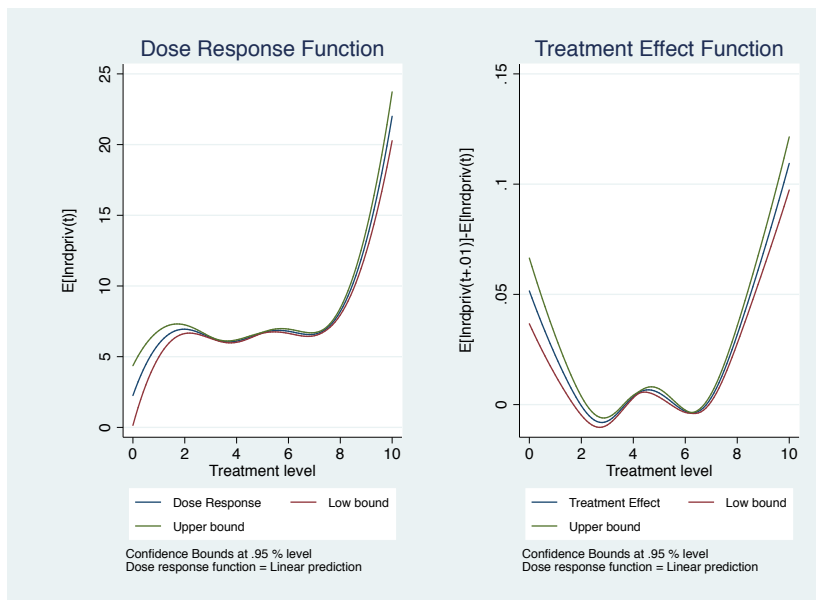


Figure 28: Continuous Treatment Matching: Dose-Response and Treatment Effect - Differences in % changes of Private R&D - Subsidy under Tax Credit

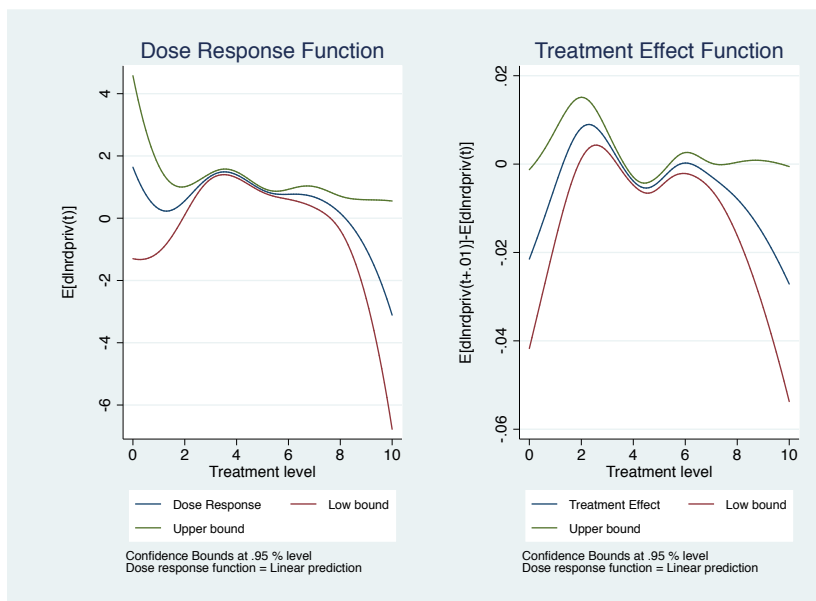


Figure 29: Exact Matching: ATT Estimates - Differences in log-levels of Private R&D - Treated (Small) vs Controls - Subsidy

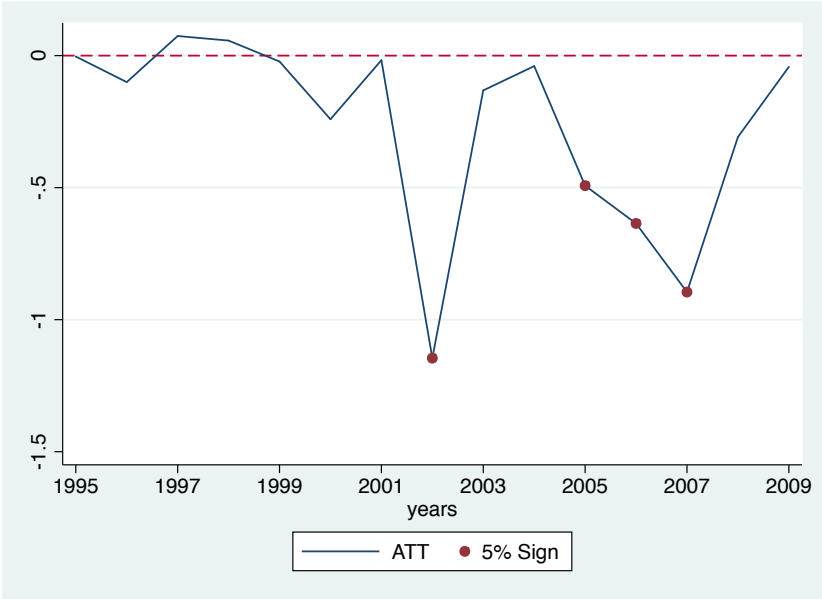


Figure 30: Exact Matching: ATT Estimates - Differences in log-levels of Private R&D - Treated (Medium) vs Controls - Subsidy

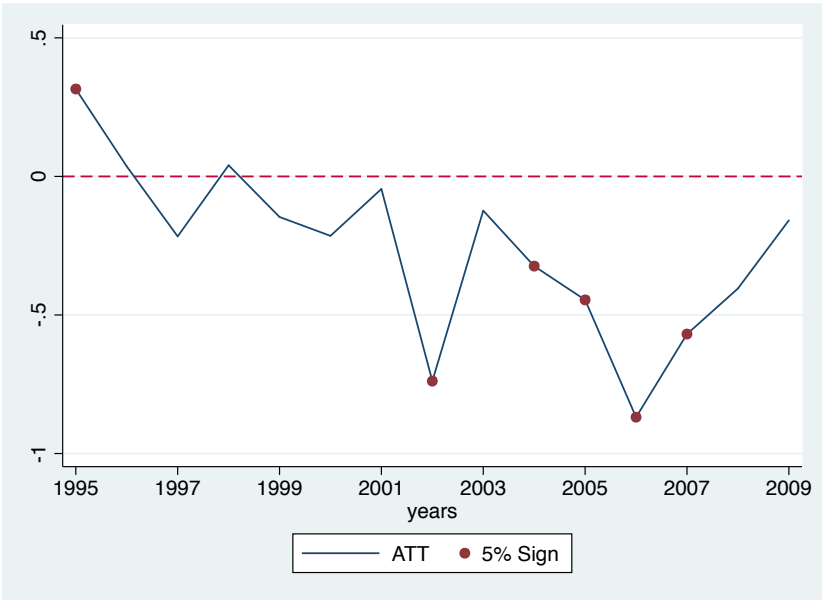


Figure 31: Exact Matching: ATT Estimates - Differences in log-levels of Private R&D - Treated (Large) vs Controls - Subsidy

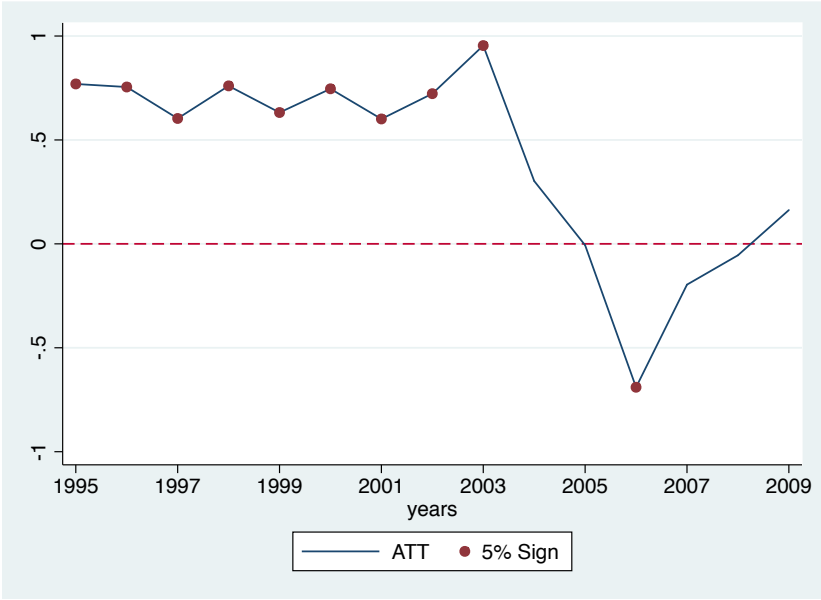


Figure 32: Exact Matching: ATT Estimates - Differences in log-levels of Private R&D - Treated (Medium) vs Controls (Small) - Subsidy

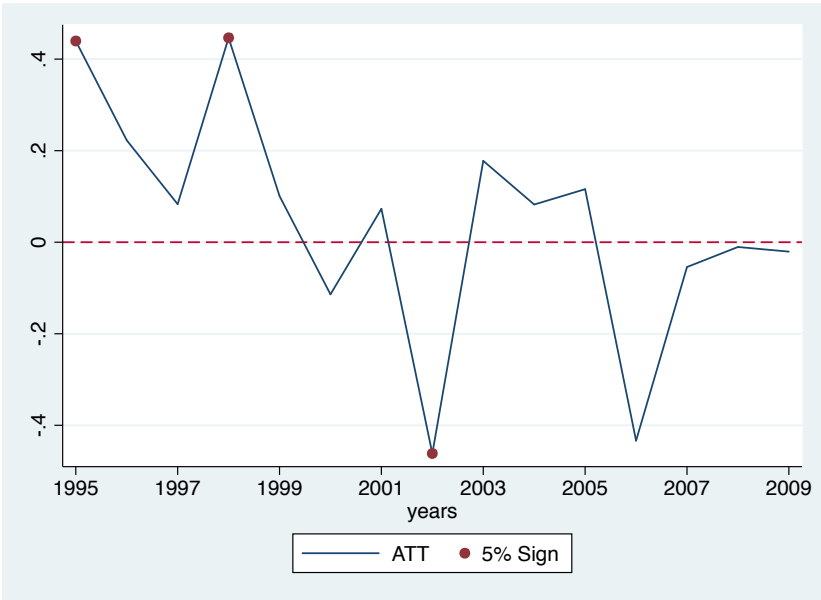


Figure 33: Exact Matching: ATT Estimates - Differences in log-levels of Private R&D - Treated (Large) vs Controls (Medium) - Subsidy

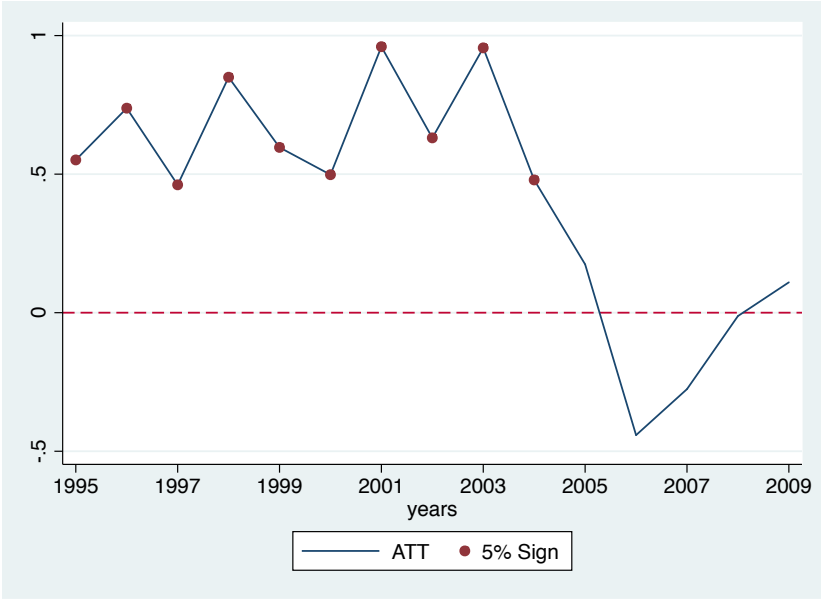


Figure 34: Exact Matching: ATT Estimates - Differences in % changes of Private R&D - Treated (Small) vs Controls - Subsidy

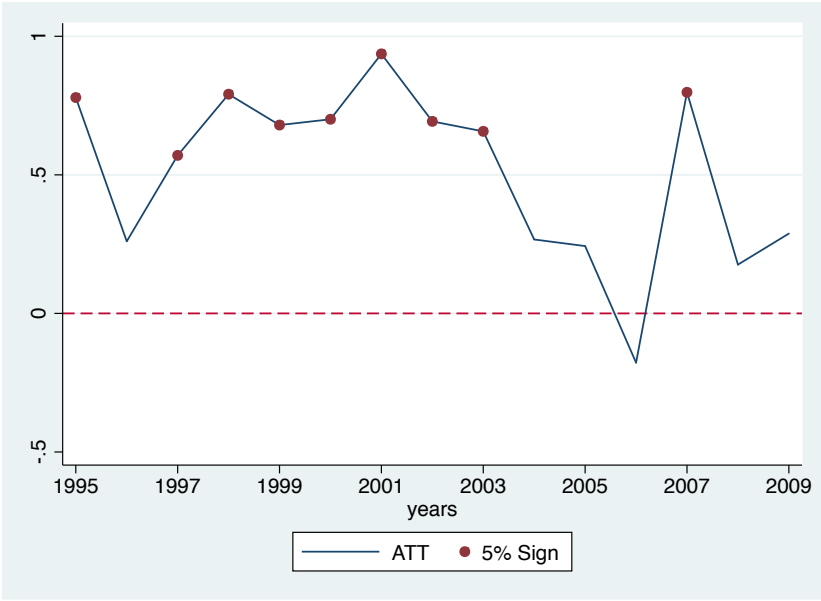


Figure 35: Exact Matching: ATT Estimates - Differences in % changes of Private R&D - Treated (Medium) vs Controls - Subsidy

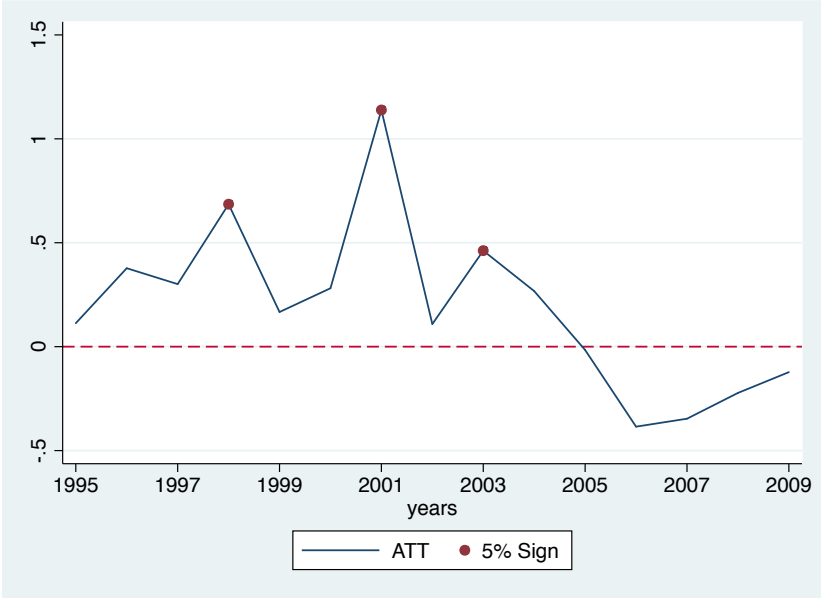


Figure 36: Exact Matching: ATT Estimates - Differences in % changes of Private R&D - Treated (Large) vs Controls - Subsidy

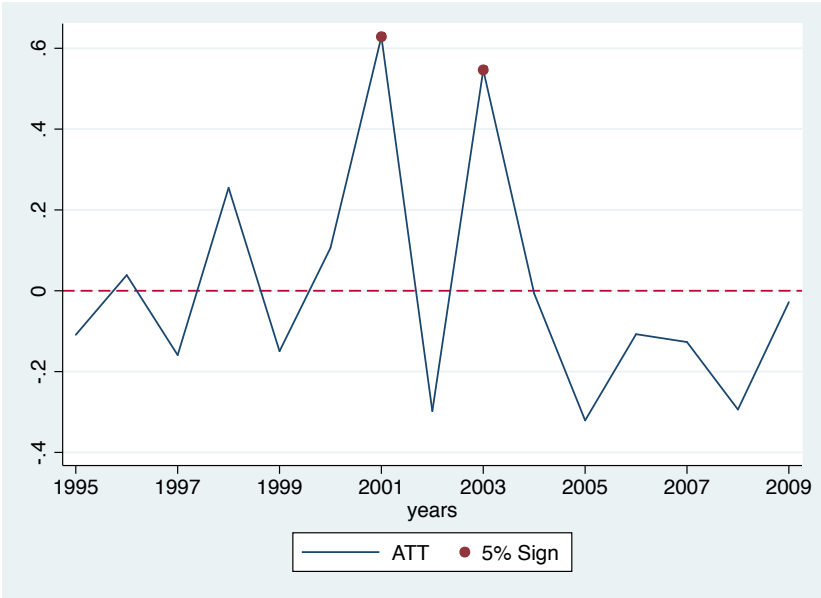


Figure 37: Exact Matching: ATT Estimates - Differences in % changes of Private R&D - Treated (Medium) vs Controls (Small) - Subsidy

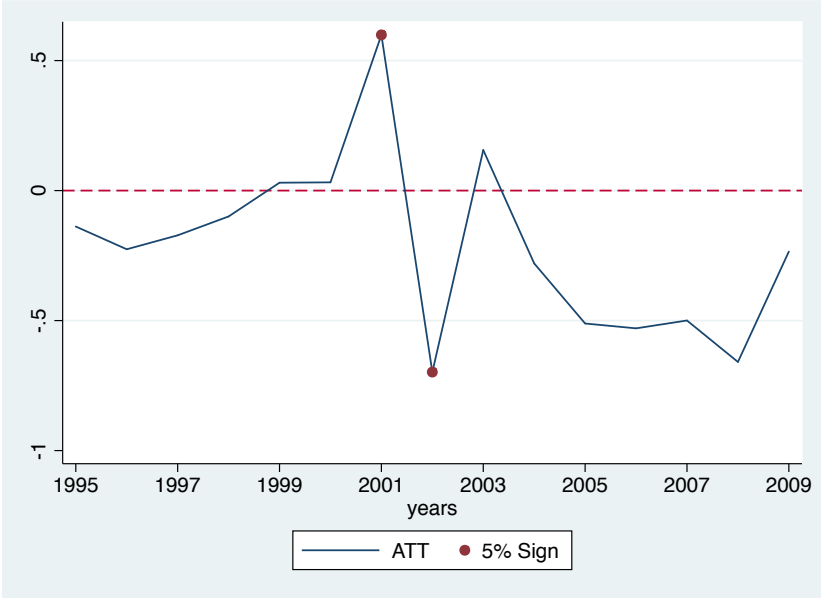


Figure 38: Exact Matching: ATT Estimates - Differences in % changes of Private R&D - Treated (Large) vs Controls (Medium) - Subsidy

