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Public R&D Policy Impact Evaluation

(Propensity Score Matching and Structural Modeling Estimations)

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To my parents:

Maman Zahra and Baba Manouchehr,

For all their sacrifice and love for their children over all these years.

& to all real peacemakers in the world who search for innovative ways to make the world a better place to live!

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Thesis Abstract

This dissertation is about public research and development (R&D) subsidies to support private firms doing innovative activities and quantitative impact evaluation of the policy on total factor productivity (TFP) change and additional R&D effort. Public R&D subsidization as a public R&D policy, beside different types of public interventions, has been widely used by governments to stimulate private R&D. These policies aim to fill the gap between the private and social rates of returns by encouraging business enterprises to spend on additional R&D, produce more innovation output and inventions, or change their innovative behavior. These changes can be carried out either individually or in collaboration with other entities. One ultimate goal of R&D policy is increasing the total factor productivity and relative performance both at firm and aggregate levels. This study deals with direct place-based public R&D subsidies and empirically measures the effects of this type of public incentives on productivity growth and R&D input additionality.

In order to evaluate the policy effect, a quasi-experimental counterfactual setting for subsidized (treated) and non-subsidized (non-treated) firms can be framed thank to the characteristics and mechanism of the local R&D program in the Province of Trento in Italy. The average treatment effect of the policy on target variables is measured for subsidized units (Average treatment effect on treated: ATET) and for the whole population of the firms (Average treatment effect: ATE), using techniques capable of tackling the problems of endogeneity and selection bias which arise in empirical evaluation studies.

Propensity score matching (PSM) and structural modeling methodologies are used to measure the effects of the R&D subsidies on target variables, TFP change and additional R&D expenditure, respectively. The former approach is non-parametric and does not assume a functional form for the effect of policy on R&D and productivity change, while the latter models the optimizing behavior of the firm (agent) and the public agency, searching for an equilibrium in a pre-determined game theoretical framework. Although the PSM method takes advantage of no pre-defined structure assumption, however and in contrary, the structural model with simultaneous equations, takes into account the effect of unobservables on subsidized firms' selection procedure, beside R&D spillovers effect.

In order to design the evaluation framework to estimate ATE and ATET on the target variable of interest (TFP change), we have built a firm-level panel dataset (maximum 5 years of information) constructed by combination and merge of datasets related to public (provincial) R&D policy, firms' characteristics, firms' R&D activities and TFP change measures. The time span of the dataset allows us to capture the effects in both short-term and long run, consequently tracing the short and long term effects of the R&D program. This helps us to consider the usual longer effect lag an innovation policy entails, specifically on a target variable such as productivity and a treatment such as innovation incentive, which the effects may take time to be realized in comparison with other types of outcomes and investment policies. The dataset represents the outcome of a long process of combining and merging various datasets related to firms' financial statements and balance sheet (AIDA: Italian company information and business intelligence) and APIAE's R&D policy information provided by ISPAT.

TFP change and its decompositions, technical efficiency change and technological frontier change are realized using Malmquist Data Envelopment Analysis (DEA) method. DEA takes a system approach towards the firm as decision making unit (DMU) and only applies the input(s) and output(s) measures to calculate the relative (in)efficiency of the firms. Malmquist method based on index theory, captures the (in)efficiency change and the technological frontier movement within a time interval. TFP change measures are calculated by CRS output-oriented DEA dual model using a new package introduced in STATA software and merged into the reference dataset described previously.

To sum up, after the formation and construction of dataset by combining and merging different datasets, treatment effect analysis is carried out using PSM nearest neighbor and kernel estimators. The balancing property satisfaction on pre-treatment observable factors (age and size in our setting) is primarily investigated and propensity distribution graphs have been also provided. Taking into account the dataset features, R&D subsidies effect is measured for manufacturing and ICT industries (using 4 techniques to measure both ATE and ATET), beside low-medium technology and high-tech industries classifications (Both ATE and ATET). Moreover, the subsidies effect on TFP measures have also been measured for different categories of selection procedures. Results show heterogenous and mixed effect of R&D subsidies based on different settings of evaluation (sectors and selection categories), targeted outcome, PSM method (different

PSM algorithms for nearest neighbor and kernel) and time of the effect (short-term or long run). The complete results have been discussed in detail in the related sections in chapter three.

To address the effect of unobservable factors, beside spillover effect on R&D subsidies allocation and the effect on outcome, a structural model is estimated using a cross-sectional dataset. The dataset is formed by merging R&D policy-related (linked to Provincial Law LP 6/99 enforced by provincial agency for the promotion of economic activities :APIAE) dataset and firms' determinants provided by ISPAT (Statistical institute of Province of Trento).This approach complements the drawbacks due to estimation using PSM methodology. However, the pre-defined functional form for equations is a limitation of this approach. The structural model applied includes application decision, selection (subsidies allocation) and R&D investment equations to be turned into econometric equations for empirical estimation. The context and dataset features allow for different empirical modifications with respect to the benchmark model applied. The results determine the effect of firm (project) characteristics on all stages of the subsidization game. Size, age, exporting status, board size and sector are main factors being investigated. The results show not only there is no additional R&D expenditure, but also some crowding out of subsidies occurs. The base model is determined in such a format which makes it possible to evaluate the spillover effect and spillover rate of R&D spending as well. The results show that on average half (50%) of each euro spent on R&D spill overs.

The results shed light on the effects and impacts of a place-based R&D policy on TFP change ,R&D additionality and spillovers, while suggesting policy implications to the local public authorities. Furthermore, the design and process of impact evaluation using two different complementary approaches in a new context on a different target variable (TFP change in addition to classical input additionality variable) can be referred and applied in any policy evaluation related studies.

In the following, chapter one deals with the theoretical and empirical reasons for the existence of different public R&D policies based on Schumpeterian growth theory, spillovers effect and tackling market failure. It further provides a review of R&D and innovative activity indices at different levels of analysis (regional, national and international) and reviews the literature of empirical innovation policy evaluation studies related to the effect of R&D policy on additionality.

The review concerns both micro and macro perspectives in approaching public R&D policy and the impact of the policy on additionalities and TFP growth. Studies in R&D policy usually concern either the macro growth accounting approach and measure the effect of R&D policies on aggregate growth indices regardless of pointing out to micro foundation effects leading to the aggregate level changes or they only focus on the micro-econometric firm-level evaluation without addressing the relationship between firms' additional R&D activities and the economic growth. Moreover, the R&D activities expenditure and growth indices at international, EU, national (Italy) and regional (Trento Province) have also been briefly pointed out and tracked over time, to realize the practical importance of R&D incentives.

In order to introduce and spot the areas this research addresses, the traditional market failure and the logic and reasons behind public R&D policies (aimed at increasing positive externalities and R&D spillovers) and subsequently different innovation policy instruments and their interaction with firms' R&D decision making have been reviewed. This provides a comprehensive perspective over the importance and the forms of R&D policies.

Chapter two primarily discusses about the effect of R&D subsidies on TFP change. The discussion addresses the relationship between R&D and total factor productivity (TFP) as a channel which subsidies may affect TFP. In addition, other channels and interactions which can explain the effect of R&D subsidies on TFP change and the components of TFP change, will be investigated and discussed. Afterwards, in line with the review of the previous chapter, the empirical literature of studies dealing with evaluation of the effect of R&D subsidies on TFP (as a different outcome variable from additionality variables discussed in the previous chapter) will be reviewed. This theoretical background helps us to shape the R&D policy evaluation framework to investigate the direct casual impact of R&D subsidization policy on target outcomes including TFP change (Chapter 3) and R&D expenditure (Chapter 4). Finally, taking into account the evaluation framework, we hypothesize the research questions based on the theoretical concepts and literature review discussed through the previous and current chapters.

Chapter three measures the effect of the provincial R&D subsidies on technical efficiency and technological frontier change as the decomposing elements of productivity change. It empirically measures the impact of R&D subsidies on productivity change using counterfactual treatment effect analysis. Malmquist Productivity Index (MPI) based on the non-parametric method of Data

Envelopment Analysis (CRS output-oriented dual DEA model) is applied to measure the productivity change and the disentangled elements of productivity change. The chapter has contributed to the literature in some different aspects.

The main focus of this chapter is measuring the effects of R&D subsidies on decomposing elements of TFP, technical efficiency and technological frontier change. In the whole literature, there is only one other similar work in which the effects of R&D subsidies on TFP decomposed components have been assessed. There are few other papers in which they measure the impact of other type of investment subsidies (mainly capital subsidies) on targeted variables of TFP decompositions. However, they all use a parametric approach to measure the TFP components in contrary to non-parametric Malmquist DEA method applied in our study making no predefined assumption about the production function.

The subsidies effect evaluation is implemented using both PSM nearest neighbor and kernel methods (to check the robustness) to measure the average treatment effect of R&D subsidies on subsidized (treated) and all (the population) firms labeled as ATET (average treatment effect on treated) and ATE (Average treatment effect), respectively. The analysis is mainly carried out in manufacturing and ICT sectors as two main sectors in which R&D incentives allocations occur. The elaboration on classification of firms in different main industries based on ATECO 2007 system of firms' economic activity coding has been carried out. It has also been defined and described in detail how 6-digit industry code is categorized into sectors.

Another important feature of this study different with a considerable share of empirical literature, is construction of a panel dataset on subsidies allocation and firms' characteristics which allows us to capture the effect of the policy both in short term and long run (maximum of 5 years). Moreover, the effect of the evaluation based on two different types of selection and allocation procedures (automatic, evaluative (combined with negotiation method) is implemented.

The limitations of this chapter imposed by the methodology used, are excluding the effect of unobservable factors on selection process and not taking into account the spillovers effect. Consequently, Chapter's four structural modeling puts effort to overcome these restrictions and suggest a complementary approach.

Chapter four empirically estimates an equilibrium oriented structural game model to investigate the relationship between firms' characteristics with application cost (application decision equation), spillover rate (subsidization equation) and R&D investment (investment equation). The chapter reviews, modifies and estimates a structural model describing the mechanism through which the R&D subsidization policy influences R&D activity and the R&D spillover rate. The empirical contribution of this chapter is proposing a simplified model of a reference 4-staged game model with a Nash Bayesian Equilibrium (NBE), based on the contextual setting of the region under study and data availability. The advantage of using this structural model is the ability to assume spillovers effect. This optimization approach relaxes the incapability of evaluation approach used in Chapter three to assume the presence of spillover effect due to the violation of Stable Unit Treatment Value Assumption (SUTVA). Moreover, chapter four takes into account the effect of unobservables on selection procedure and targeted variable, while in chapter three the unobservables are assumed uncorrelated with selection (subsidy) variable and the outcome. Nevertheless, opposed to structural modelling, the method used in chapter three does not assume any parametric form to evaluate the impact. Hence, chapter three and chapter four complement each other in measuring the impact of R&D policy on targeted variables.

The empirical evaluations and results of both final chapters are explained and concluded in the related essays. Moreover, the features and contribution of chapters will be restated in the abstract at the beginning of each chapter.

Chapter 1:

R&D policy evaluation: Theoretical background and empirical review

Abstract

Chapter one predominately discusses the perspectives and approaches related to theoretical background regarding public R&D policy, followed by a review of change of practical measures related to R&D input and output over time at regional, national (EU) and international levels. The chapter mainly deals with theoretical and empirical logic behind different public R&D policies embodied into Schumpeterian growth theory and in line with innovation spillovers and tackling market failure. After all, it reviews the literature of empirical innovation policy evaluation studies related to the effect of R&D policy on additionality due to investigation of the hypotheses related to Chapter four.

1. Why innovation policy: Theoretical background

1.1 Innovation activity and economic growth

Innovation activity[1] is considered as the main element determining steady state (long-run) economic growth, based on the endogenous growth theory originated by Schumpeter's theory of creative destruction[2]. The creative destruction introduced by Schumpeter (1942) as an essential fact about capitalism refers to the phenomenon in which "prospect of more future research discourages the current research by threatening to destroy the rents created by current research" (Aghion & Howitt, 1998). Schumpeter (1942) describes "how capitalism administers existing structure is essentially irrelevant" since "the relevant problem is how it creates and destroys them". Therefore, an endogenous source of energy within the economic system would, of itself, disrupt or destroy any equilibrium attained. This is in contrast to Walras' view that the economic system

[1] Innovation activity is defined as "[A]ny systematic and creative work undertaken in order to increase the stock of knowledge, including knowledge of [hu]man [kind], culture and society, and the use of this knowledge to devise new applications." (OECD-Eurostat manual on standard practice for statistical surveys on R&D activities_ Frascati Manual, 6th edition, 2002). [The 7th edition has been published in 2015: Frascati Manual - 2015 Edition: Guidelines for Collecting and Reporting Data on Research and Experimental Development].

[2] Schumpeter introduced the idea in his book "Capitalism, Socialism and Democracy", which his visions are still popular and discussed amongst economists especially in the recent years where capitalism has been challenged by populism. For a very recent common debate and discussion about his predictions on capitalism, see 'The Economist, Business Section: Schumpeter (Capitalism and Democracy), 24th December 2016.

is essentially passive to natural and social influences (exogenous factors) which may be acting on it. Schumpeter argues that there is an inevitable tendency of the system to disequilibrate (Mokyr in Hall & Rosenberg; 2010).

Following Schumpeter, the pioneering works of Romer (1986) and Lucas (1988) identifies the accumulation of knowledge as the source for sustained economic growth in the form of income per capita.[3] Innovation activity consisting of R&D and non-R&D activities (according to Oslo Manual[4]) counts for a channel through which the economy accumulates knowledge. In this vein, research and development (R&D)-based growth models have been developed (Romer, 1990; Aghion & Howitt, 1992, 1998). Aghion & Howitt (1998) introduce an endogenous growth model which is developed by vertical innovations, generated by a competitive research sector. These vertical innovations constitute the underlying source of growth. They determine an equilibrium using a forward-looking difference equation, in which the amount of research in any period depends on the expected amount of research in the next period. One source of this intertemporal relationship is creative destruction, which as previously noted means the rent of current research gets destroyed by the prospect of more future research (new technological innovation). In particular, the fact that private innovative firms do not internalize the destruction of rents generated by their innovations leads to a business-stealing effect which makes innovations too small.

Aghion and Howitt (2008) portray a free economy being constantly disturbed by technological innovations and in which competition is a Darwinian struggle whose survivors are those that succeed in creating, adopting and improving new technologies. Schumpeterian models on the contrary to AK model[5], takes technological change as a social process, and since the start of the industrial revolution, “people’s skills, capital equipment and technological knowledge have been rendered obsolete and destroyed by the same inventions that have created fortunes for others”. The Schumpeterian approach explains how innovation and a process of creative destruction may influence the economic growth. Innovating enterprises introduce new products or processes to

[3] The growth models enhanced by Romer and Lucas endogenized the technological advancement in contrary to Solow-Swan model which explains technological progress as an exogenous factor.
[4] Oslo manual: Guidelines for collecting and interpreting innovation data by OECD (Organisation for Economic Co-operation and Development) and Eurostat (Statistical Office of the European Communities). Oslo Manual is one of the following documents of “Frascati Family” documents developed by NESTI group (National Experts on Science and Technology Indicators).
[5] AK is the simple production function model with total factor productivity (A) and capital and human capital (K) elements. The difference with new endogenous-growth model is that AK assumes no diminishing returns to capital.

appropriate from a temporary monopoly by making old technologies or products obsolete. This destroys the rents generated by previous innovations and leads to economic growth.[6]

There have been modifications to endogenous growth theory model, known as semi-endogenous and fully-endogenous growth models. Semi-endogenous growth models, introduced primarily by Jones (1995) as a modification to Romer's model, show that the productivity growth rate is still generated endogenously through R&D, though only in a transient path rather than long-term. This happens because of diminishing returns to R&D (Kortum,1997). Semi-endogenous means that technological change is endogenous while in the long-term the growth only relies on population as the ultimate driver for productivity growth rate, implicating the economic growth as independent of government actions and public policy (Li, 2000).

The final strand of the research fully bears endogenous growth theory, eliminating the scale effect by allowing an increase in product lines (or expansion of number of firms) while the R&D for each product line keeps unchanged. Knowledge spillover (determined in the following section) affects the productivity growth rate generated by investment in knowledge and consequently investment in innovation (Peretto, 1998; Acs et al., 2004; Ha & Howitt, 2007). Fully-endogenous growth model identifies R&D intensity and population growth (not necessarily in all conditions) as factors influencing the economic growth (in terms of income per capita growth). This is in contrast with semi-endogenous models, presuming solely population growth as the predictor of the economic growth. Therefore, according to fully-endogenous model, R&D public policy will influence the steady-state productivity growth rate through stimulating firms' R&D intensity (Minniti & Venturini, 2017).

The arguments discussed above explain theories debating the relationship between innovation activity in general, and R&D in specific with the economic growth. The theories explain how a change in innovation activity influences an economy, either in the short-term or long-run. Changes in innovation activity by private business enterprises can be triggered by public interventions. Therefore, investigating the innovation policy and its impact on the determinants of economic growth provide policy makers insights about how public R&D policy may increase

[6] It is worth to remind this section focuses on the relationship between innovation and economic growth. However, there are other fundamental causes to economic growth. The role of history, geography and institutions has been studied in the outstanding work by Acemoglu et al. (2002) and Acemoglu's book of 'Introduction to Modern Economic Growth', (2008).

economic growth. This investigation can take different approaches and perspectives: macroeconomic approach takes the growth accounting perspective, industrial organization and public finance approaches focus on the policies for encouraging private sector innovation activities and investment in innovation and finally economic development approach deals with innovation systems and technology transfer. However, all these approaches measure the effect of innovation policy through applied economics approach (Cohen in Hall & Rosenberg, 2010).

This study deals with evaluating the effect of public R&D policy on private business R&D activities and productivity change as possible determinants of economic growth. Following an applied economic approach, the study addresses whether innovation policy, as an intervention of public authority in the form of industrial policy, affects productivity growth or the additional private R&D expenditure as the factors influencing economic growth.

1.2 Innovation Spillovers

Previous section addressed the potential role of public R&D policy in economic growth. Another main theoretical aspect which justifies R&D policy is related to the effect of policy on innovation spillovers. The diffusion of knowledge between firms, universities and research institutes is the main logic for incentives by public authorities in a systems approach to innovation. Creation of the new technologies as the outcome of private firms' R&D effort and transfer of this knowledge through the network is one main reason that the government supports R&D activities. Therefore, system approach besides the market failure approach supports incentives which complement private R&D spending (Clausen, 2009).[7]

A firm undertakes research and development (R&D) activities which can lead to a new technology. The technology spills over to other firms over time, propagating the knowledge obtained from the R&D activities (Konno, 2016). Spillover of knowledge as a positive externality produced by diffusion of R&D outcomes is considered as one of the main factors of economic growth (Griliches, 1992; Aghion, Howitt, 2008). Technological progress depends on the adoption

[7] In the last chapter the maximization of spillover is assumed as a main element of the goal of the public agency. Hence, the spillovers effect arrives directly in the agency's profit equation. The optimized spillover rate is the solution of an equilibrium effect of R&D subsidies for the firms doing innovation.

of the new technologies as much as their invention In reality, spillovers are likely to diffuse among all the firms across the world simultaneously.

Samandar Ali Eshtehardi et al. (2017) point out to studies by Marshall (1920), Arrow (1962), Romer (1986) and Porter (1990) which declare that the source of knowledge spillover within a region and additional innovative activities in the region, is an increase in specialization of a particular industry within a specific geographic region. They also mention Jacobs (1969) who argues that diversification of industries within a specific region is a major source of knowledge spillover as it increases the interaction of actors between industries.

Spillovers can happen in the same industry (vertical collaboration), or across sectors[8] because of user or firm R&D collaborations (one dimension of network effect or because of horizontal collaboration). It can also occur cross national via trade or foreign direct investment (FDI). Spillover effect is usually measured by considering the distance of a unit to other spilling units. The distance can be intellectual, scientific, technological or geographical (spatial) (Cerulli & Poti`, 2009). The direction of the spillovers can be measured using for example technology flow tables introduced for the first time by Scherer (1982). Jaffe (1986) introduced disembodied spillovers which the distance measure is defined as the proximity in technology which means the overlap in the distribution of the firms' patents. On the other hand, there are embodied spillovers which are categorized into direct method (technology-based) and indirect method (transaction-based) (Cerulli & Poti`, 2009). Spillovers are subjected to long lags, therefore it is noteworthy to look for the patterns of spatial correlations within and across industries and over time in measuring the spillovers (Griliches, 1957; Singh & Marx, 2013).

Finally, there is a distinction between R&D intensive inputs bought with a lower quality price compared to real knowledge spillovers. A famous example may be found in the computer industry, which usually does not appropriate fully its own benefit but lends to other industries the profit of progression. This purchase mainly affects the productivity and the purchasing industry

[8] Photographic equipment industry may not buy much from scientific instrument industry but they probably do research on the same fields and benefit much from each other's research results. However, measuring the closeness between industries requires detailed data at business-unit level due to trace the spillovers. It is difficult to say for instance 'leather' industry is closer to 'food' industry or 'textile' industry without detailed clear informative datasets.

but does not import all the R&D from the computer industry, which means the spillover measure is not real spillover happening between two industries (Tirole, J., 1988).

1.3 Market failure, public R&D policy and additionality

The main theoretical aspect used to justify R&D policy is related to traditional market failure caused by firms' underinvestment in R&D.[9] The classical market failure argument points to the gap between private and social rates of return for R&D activities (Nelson, 1959; Arrow, 1962[10]). The R&D investment by private entities is usually less than the socially optimum expected amount. The stylized fact that private rate of return is lower than social rate of return for R&D has been widely investigated by the literature[11] (Mansfield et al., 1986; Bernstein, 1989; Griliches, 1992; Jones & Williams; 1997).

Firms do not sufficiently invest in R&D when the investment rate of return will be lower than socially optimal rate. This may happen as the private enterprise mainly concerns about the revenues and gains appropriated from R&D inputs and consequently R&D outputs in order to maximize the profit out of investment in knowledge. The source of this concern arises from that knowledge becomes common and public good after being produced and the knowledge producing firm might not sufficiently benefit from the temporary monopoly caused by her invention. The other point is that knowledge can spill out and diffuse into the network as positive externalities, i.e. spillover effect or network effect. Thus, before a private firm fully appropriates from its innovation output (product or process innovation), other entities imitate the output dependent to their absorptive capacity. Hence, this market failure discourages the private firm to invest optimally in R&D (Arrow, 1962; Griliches, 1992).

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[9] In a historical point of view, before industrial revolution, technological changes (caused by investment in innovation) were undermined by either greedy of poorer or violent tax collectors. After industrial revolution and consequently industrial enlightenment, Francis Bacon (1744) spreads the idea that useful knowledge is rich storehouse for the glory of the creator and relief of the man's estate. After this period when still Britain was the leading industrial nation, it comes the transition to modern growth (1830_1880) while because of progress in transport technology mainly railroads*, the "push" for improvement* dominated.

[10] Arrow (1962) discusses about non-perfect appropriability of knowledge representing the public good as the reason for this gap.

[11] It has been widely approved by empirical studies that R&D social rate of return is higher than R&D private rate of return and the private rate of return is higher than other more "conventional types of investment" rate of returns including capital investment (Martin, 2002). One reason referred to rent-seeking literature can be overbidding problem proposed by Fundenberg and Tirole (1987).

In other words, if the firm invest additionally in R&D, the society including competitors can benefit more than the firm due to lack of full appropriability of R&D activity due to knowledge spillovers or innovators' inability to price-discriminate (Fölster, 1995).

Hall (2002) points out to another reason for market failure, which occurs due to the wedge and the gap between the firm investing in innovation and the external investor for the expected rates of return related to the R&D project. This gap leads to the higher cost for external capital, specifically for the small, young and financially constrained firms. In addition, firms doing R&D are investing in knowledge as an intangible investment and public good. The liquidity constraints of the firms is particularly important for investment in intangible inputs subjected to uncertainty and information asymmetry (Hall & Lerner, 2009; Bronzini & Iachini., 2014).

In other words, being all other factors equal, firms that encounter more difficulties in financing their projects usually submit their proposals to benefit from public funds. These difficulties can happen because of informational asymmetries leading to higher costs for capital and more barriers to access the capital markets.

At the same time investing in innovation is riskier than investment in tangible assets. The risk originates from the facts that innovation requires more expertise in comparison with other types of investment. Furthermore, as mentioned the knowledge can leak and spillover, therefore the firm might not be willing to share the information of its R&D project with intermediaries or in the form of collaboration. Moreover, shortcomings in network knowledge flows and lack of interactions between innovators, mainly due to reluctance of entities to cooperate in R&D projects can also discourage firms in doing additional R&D (Kastelli & Caloghirou, 2004; Lundvall & Borrãs, 2005; Bond & Van Reenen, 2007; Hall & Lerner, 2009). These all can increase the risk of failure for an innovative project.

The social planner or public authority, aiming at growth and social welfare maximization, is eager to encourage research and development by institutions such as firms, research institutions and universities, both at micro and aggregate level. In order to increase innovation activities that lead to higher social welfare for the whole society, incentives are offered to firms conducting R&D individually or in collaboration. Incentives can be in the forms of grants, tax incentives, or government contracts with R&D performing firms in the private sector, often called as procurement contracts[12]. Public authorities fund and subsidize R&D as a policy or intervention to support innovation activities by entities. Innovation incentives in general, and subsidies for private R&D activities in specific, are policies or programs to compensate for market failures (Busom, 2000; David, Hall & Toole, 2000).

The society and (let us subsequently assume) the public authority, benefit from R&D output because of the spillover effect leading to consumer surplus. At the same time, private firms' appropriability and R&D rate of return matter for public agency. As long as private firms are also considered as a part of the society. Therefore, the government is responsible to design a framework to maximize spillover (in terms of positive externalities), while simultaneously setting up the institutions to promote the private firm to invest more in knowledge (R&D). This all implies that public agency intervention to encourage private R&D is required even in a market system. The instruments used to reinforce this intervention will be more explained in the following sections in current chapter.

The main question for policy makers is whether the adopted innovation policy promotes a firm to undertake an R&D project or to invest additionally in existing R&D project(s) that the firm would not have undertaken without the intervention (Jaffe, 2002). In other words, public authority is interested to evaluate whether public R&D spending is a complementary or a substitute[13] for private R&D spending as R&D input. Input additionality happens when the firm spends more than the amount it would have spent without the incentives on R&D projects. In this case, the policy affects positively on firms' additional investment (complementary or crowding-in effect). On the other hand, if the firm applies and substitutes the fund received to spend on the R&D project that it would have done even without the public support, there will arise input crowding out effect[14].

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[12] According to David et al. (2000), "[G]overnment R&D contracts are financial outlays to procure research results that are expected to assist the public agency in better defining and fulfilling its mission objectives." These contracts are in the shape of awards set by public authority for for-profit firms to push firms to perform R&D in the area in which the government is interested. This category covers much of the public aerospace and defense expenditures.

[13] Complementarity or additionality is the case in which the subsidized firm undertakes additional effort (investment) in doing R&D project(s), whereas it would not have done the same if it was not awarded the subsidy. Substitution or crowding-out is the case in which the firm substitutes a proportion of the incentive with the amount of money which would have been spent even in the case of no subsidy.

[14] The term 'free riding' in this context also means spending the subsidies on projects which would have been carried out even without the incentives or spending the granted amount in other activities (Bronzini & Iachini, 2014).

Besides input additionality, additionality can also be referred to output additionality and behavioral additionality. The former refers to the production of more innovation outputs such as inventions and patents. The latter refers to the R&D activity which firm would have done even without the subsidy but in a different way (doing the research differently such as collaborative R&D or applying different innovation methods).

Output additionality is realized when the private firm introduces a new innovative output (product or process innovation) which would have not been obtained without being granted. “Output can either be defined in terms of direct firm-level innovation outputs like patents, papers, prototypes or in terms of indirect firm-level innovation outputs such as the introduction of new products or the application of new processes and services.

Behavioral additionality first introduced by Buisseret et al. (1995), also called as second-order additionality by Autio et al. (2008), aims to complement and not to replace the traditional input and output additionality concepts. It follows an evolutionary approach towards innovation, is interpreted as cognitive capacity additionality and refers to the impact of public R&D support on the firms R&D strategies or decisions on scale, scope, investment timing, etc. (Barbieri et al., 2012). The subsidies can change the innovation and R&D behavior of the firm and the R&D strategies taken by the firm. This means that temporary subsidies (and R&D incentives in general) to the firms can influence the firms’ long-term R&D effort and commitment to innovate (Clausen, 2009).

Bronzini and Piselli (2016) take into account spending more on research rather than development, starting new collaborations and change in R&D conducting management as examples of behavioral additionality. Data collection for this type of additionality is more challenging as the other types of additionalities are more quantifiable (Barbieri et al., 2012).

Effective and efficient innovation policy requires public authorities to realize the impact of the policy on innovation activities and to understand the mechanisms and channels through which input, output and/or behavioral additionalities are linked to each other and investigating how the policy is related to additional innovation activities and other target variables.

In sections related to theoretical background, the position of innovation activities in the growth theories has been spotted. Afterwards, the spillover effect as a main criteria for the policy maker and an important phenomenon happening in the network of innovators (and non-innovators) has been addressed. The famous market failure related to private firms' R&D underinvestment together with different public policies to tackle this failure in order to stimulate different types of additionality were also discussed. Now, the dissertation's theoretical and practical review can be directed towards more detailed explanation of R&D policies and finally evaluation of these policies as the main focus of the thesis.

However, beforehand we turn into these topics, it seems necessary and it can add value to review and discuss the R&D activities and R&D policies in a more practical perspective according to input and output R&D activity. Therefore, as our empirical data in this work links to a provincial context in one of the main players and founders of EU, we review the goal and programs of European Union and some indices related to innovative activities of EU countries in addition to Italian provinces. The main focus will then tend to the measures related to our case study, Trento Province in Italy.

2. Innovation (R&D) activity and R&D policy in practice

2.1 R&D and European perspective (Lisbon Strategy and Europe 2020)

Innovation (R&D) activity as a motive for the economic growth and higher productivity has been a core concept for Lisbon Strategy 2000_2010, which has set a 3 percent of R&D expenditure as a percentage of gross domestic production (GDP) by 2010 (European Commission, 2000)[15]. However, according to Eurostat[16] data, there has been a decreasing investment in R&D in several European member states in this period. The average R&D expenditure barely reached the average of 2% of the GDP in the EU-27 as a whole by 2007.

Although there have been improvements in unemployment rates through 2010, the goals related to innovation activities and R&D expenditure increases by member states set by the Lisbon Strategy have not been fulfilled. Moreover, the Commission stimulates knowledge and innovation through greater investment in R&D and information and communication technologies (ICT), as a

[15] This amount is still one of the Europe 2020 program headline targets (European Commission, 2010).

[16] Eurostat first established in 1953 is the statistical office of the European Union and Directorate-General of the European Commission, situated in Luxembourg. Its mission is to provide high quality statistics for Europe.

major objective to deal with "employment and productivity growth lagging behind due to limited investment both in ICT, as well as in research and development" (Rodriguez et al., 2010).

2.2. R&D expenditures to GDP[17] ratio at international, national and regional levels

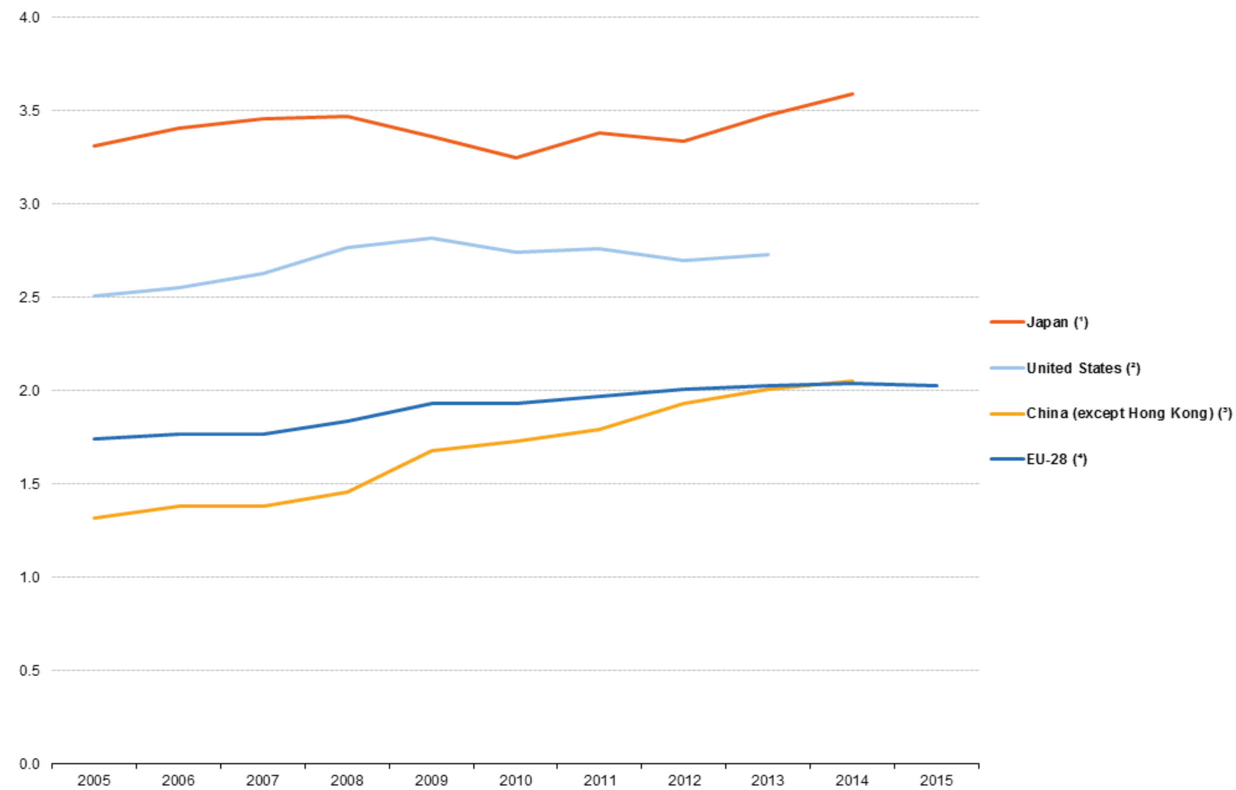
Hereby, it is worth to review statistics related to the R&D expenditures for EU28[18] at the international level, followed by the statistics at European and finally regional levels in Italy for specific periods of time. This will provide insights about R&D expenditures in Italy compared to other states, as the case of this study relates to a province in Italian context.

Figure (1) extracted from Eurostat shows the changes for gross domestic expenditure on R&D to GDP ratio for EU28 compared to China, Japan and United States over the period between 2005 to 2015. The R&D spending for EU has gradually risen since 2005, followed by a close to zero change from 2012 onwards, while others have experienced more versatile changes over the period. China increased the ratio on a more stable trend from a lower point in 2005, catching up Europe by 2012. Japan and USA have always performed respectively higher than 3.2% and 2.5% since 2005. The graph brings up the idea that the EU needs effective and efficient R&D policies in order to ramp up the average gross domestic expenditures on R&D for being more competitive.

Figure (2) defines the gross domestic expenditure on R&D the same as previous figure (1) but separately for each EU-28 countries besides some other states outside the European Union for the years 2005 and 2015. Except Sweden, Finland, Luxembourg and Croatia, other EU28 states have experienced an increase in total expenditure on R&D, point to point in time (2005-2015).

Figure (3) focuses on the changes of the average EU-28 R&D expenditures based on different sectors. The business (private) sector holds the highest share. Interestingly, the higher education sector possesses a larger part of the GERD/GDP percentage than the government sector.

[17] "Research and experimental development (R&D) comprise creative work undertaken on a systematic basis in order to increase the stock of knowledge, including knowledge of man, culture and society, and the use of this stock of knowledge to devise new applications. R&D expenditures include all expenditures for R&D performed within the business enterprise sector (BERD) on the national territory during a given period, regardless of the source of funds. R&D expenditure in BERD are shown as a percentage of GDP (R&D intensity)." [Eurostat, 2017]
[18] The European Union (EU) comprises 28 member states.



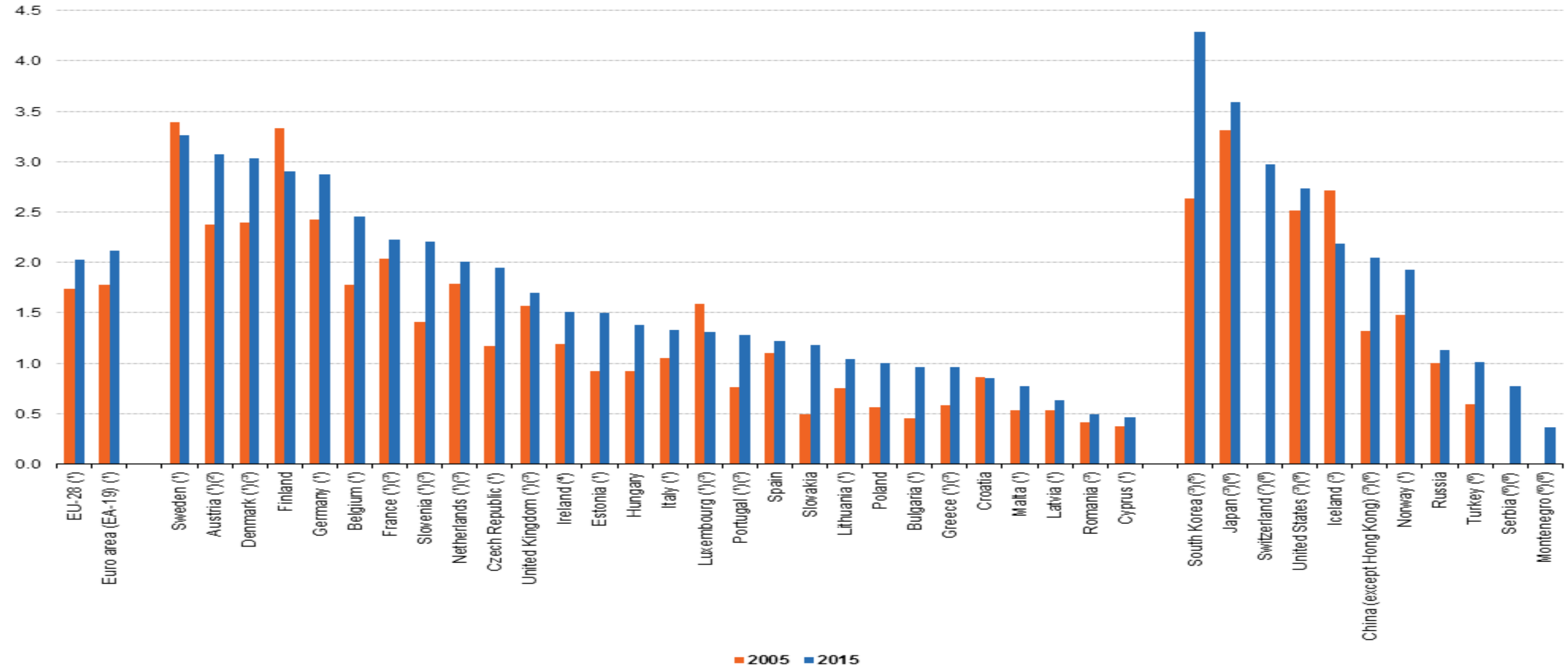
(1) 2008 and 2013: break in series. 2015: not available.
(2) Excludes most or all capital expenditure. 2013: provisional. 2014 and 2015: not available.
(3) 2009: break in series. 2015: not available.
(4) 2015: provisional.
Source: Eurostat (online data code: tsc00001)

Figure 1. Gross domestic expenditure on R&D, 2005–2015 (% of GDP)

Source: Eurostat

The same index illustrated in figure (3) for average EU28, is shown for each state in 2015 besides some other Non-EU28 countries in figure (4). Private (business enterprise) sector share of R&D expenditures represents the largest part of the total expenditures for Italy like the same pattern for many other countries. However, the share of higher education is interestingly higher than business sector in countries like Estonia, Lithuania and Cyprus.

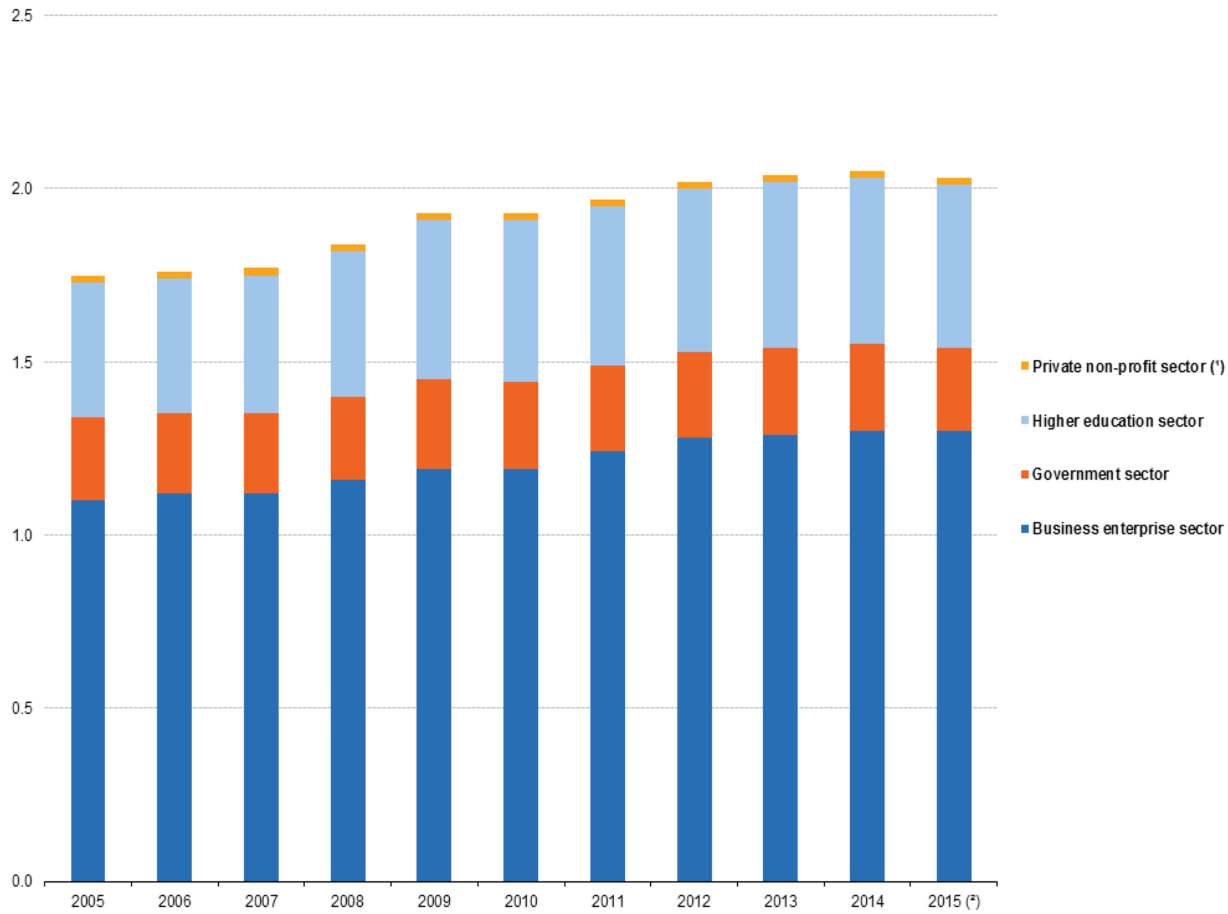
Switzerland, Denmark, and Sweden bear the lowest proportions of government expenditures in the total GERD ratio. Business enterprise sector and higher education sector handle almost the whole R&D expenditures. Although the government has not participated largely in R&D, but these countries have obtained high shares of GERD/GDP.



Note. When definitions differ, see http://ec.europa.eu/eurostat/cache/metadata/en/rd_esms.htm.
(¹) 2015: estimate or provisional.
(²) 2005: estimate.
(³) Break in series.
(⁴) 2014 instead of 2015. 2014: estimate.
(⁵) 2005: definition differs. 2014 instead of 2015.
(⁶) 2014 instead of 2015.
(⁷) 2012 instead of 2015.
(⁸) 2005: not available.
(⁹) Definition differs. 2013 instead of 2015. 2013: estimate.
Source: Eurostat (online data code: rd_e_gerdtot)

Figure 2. Gross domestic expenditure on R&D (GERD%) for different states, 2005 and 2015 (% of GDP)

Source: Eurostat



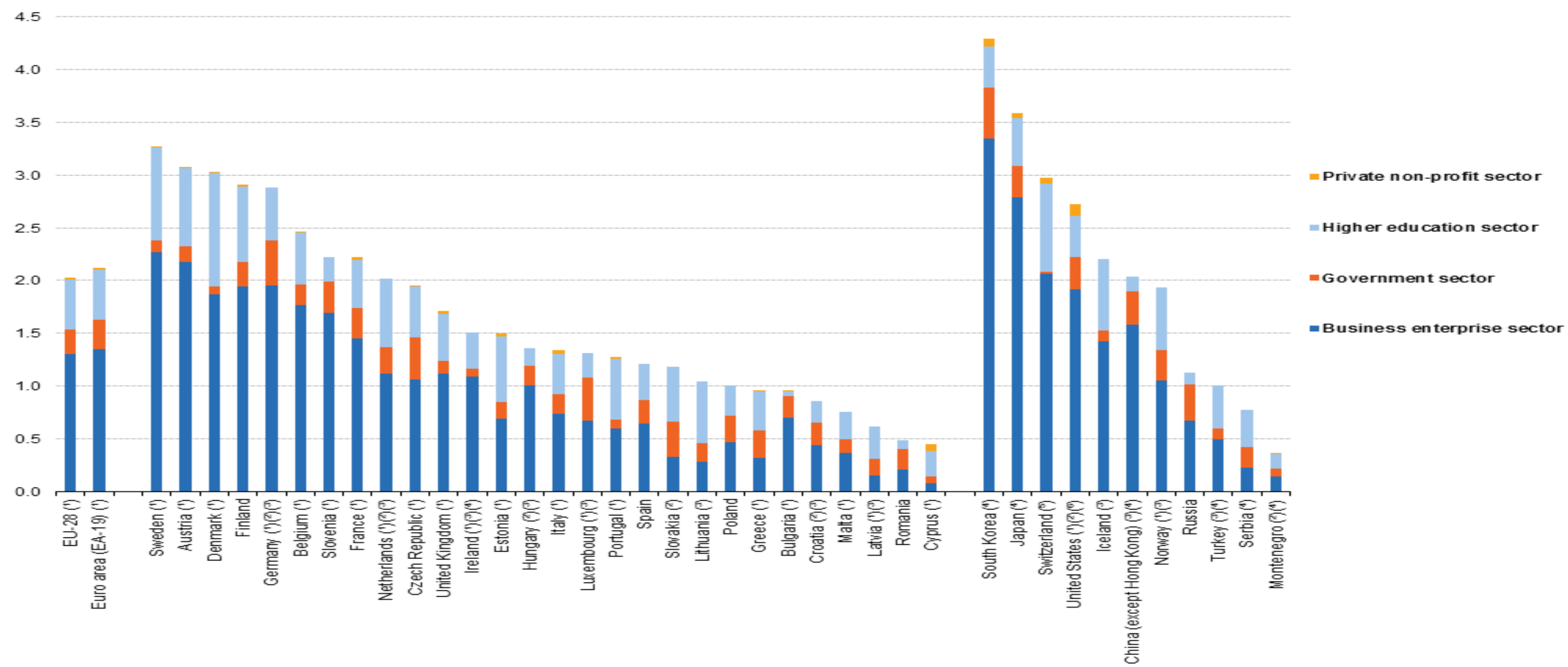
(¹) 2005–2014: estimates.
(²) Provisional.
Source: Eurostat (online data code: rd_e_gerdtot)

Figure 3. The share of gross national expenditures for R&D to GDP (GERD%) for different sectors, 2005-2015

Source: Eurostat

Figure (4) shows the amount of gross national R&D expenditures to GDP at national level for year 2015. R&D expenditure in the EU-28 countries accounted for 2.03% of the EU GDP.[19] Figure (4) identifies the total national R&D intensity as one of the key factors of Europe 2020 strategy in the forms of gross national R&D expenditure to GDP[20] (GERD%) and business (private) enterprise R&D expenditure to GDP[21] (BERD) within the European context.

[19] For Euro area the amount is slightly higher as 2.12%.
[20] The gross domestic expenditure on R&D (GERD)
[21] Business enterprise expenditure on *R&D (BERD)*



Note. When definitions differ, see http://ec.europa.eu/eurostat/cache/metadata/en/rd_esms.htm.
(1) Estimates or provisional.
(2) Definition differs.
(3) Private non-profit sector: not available.
(4) 2014.
(5) 2012.
(6) 2013.
Source: Eurostat (online data code: rd_e_gerdtot)

Figure 4. Gross domestic expenditure on R&D (%GERD) by sector, 2015 (% of GDP)

Source: Eurostat

Sweden (3.26%), Austria (3.07) and Denmark (3.03%) are the only countries performed above the 3 percent ratio in 2015. These were followed by Finland (2.9)[22], Germany (2.87%) well above Belgium (2.81%), France (2.23%), Slovenia (2.21%), the Netherlands (2.01%), Czech Republic (1.95%), Norway (1.93%) and the United Kingdom (1.7%).

As one of the largest economies in the EU, Italy (1.33%) is carrying out R&D less than Ireland(1.5%), Estonia (1.5%) and Hungary (1.38%) whilst higher than Luxembourg (1.31%), Portugal (1.28%) and Spain (1.22%). The R&D intensity (the ratio of GERD to GDP) increased from 1.31% in 2013 to 1.38% in 2014 and then decreased to 1.33%.[23] Italy's 2020 target of 1.53% is not out of reach; however, the country still should spend more on R&D to achieve the 3% target of the 2020 strategy, currently matched only by two Scandinavian economies and Austria.

The total R&D expenditure to GDP (GERD/GDP) and business R&D expenditure to GDP (BERD/GDP) at EU national level for the year 2012, have been also shown in figure (1.a.1) in appendix (1.a) and discussed using a different source (ISTAT)[24] from Eurostat. These additional data description together with previous figures can depict a general comparative picture of the R&D expenditure at all sectors and private business sector at national level.

The research in this paper relies on firm-level data from the autonomous province of Trento, Italy. It therefore requires a general perspective on R&D expenditure at regional level in comparison with other regions in the state. Figures (5) and (6) show the annual ratios of total R&D expenditure (GERD%) and business R&D expenditure (BERD%) to GDP for different regions. The change of the ranking can also be traced over time. In 2001, Trento province shows a low amount, slightly higher than 0.6% of total R&D expenditure/GDP ratio, while this year is just the outset for the first R&D subsidy installment related to new provincial law LP 6/99 (set in 1999). The law commits the province, to allocate R&D subsidies to enterprises operating in the province for R&D applied research projects.

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[22] Finland has decreased the amount of GERD% from 3.75% in 2009 (as the highest amount ever recorded) to 2.9% in 2015.

[23] To see the detailed GERD% to GDP measures check: http://ec.europa.eu/eurostat/tgm/refreshTableAction.do?tab=table&plugin=1&pcode=tsc00001&language=en

[24] ISTAT report based on The European system of national and regional accounts (ESA 2010). ISTAT (In Italian: Istituto nazionale di statistica) is a public research organization founded in 1926 as the main producer of official statistics at the service of citizens and policy-makers. ISTAT has been performing the role of directing, coordinating, and providing technical assistance and training within the National Statistical System (Sistan) since 1989.

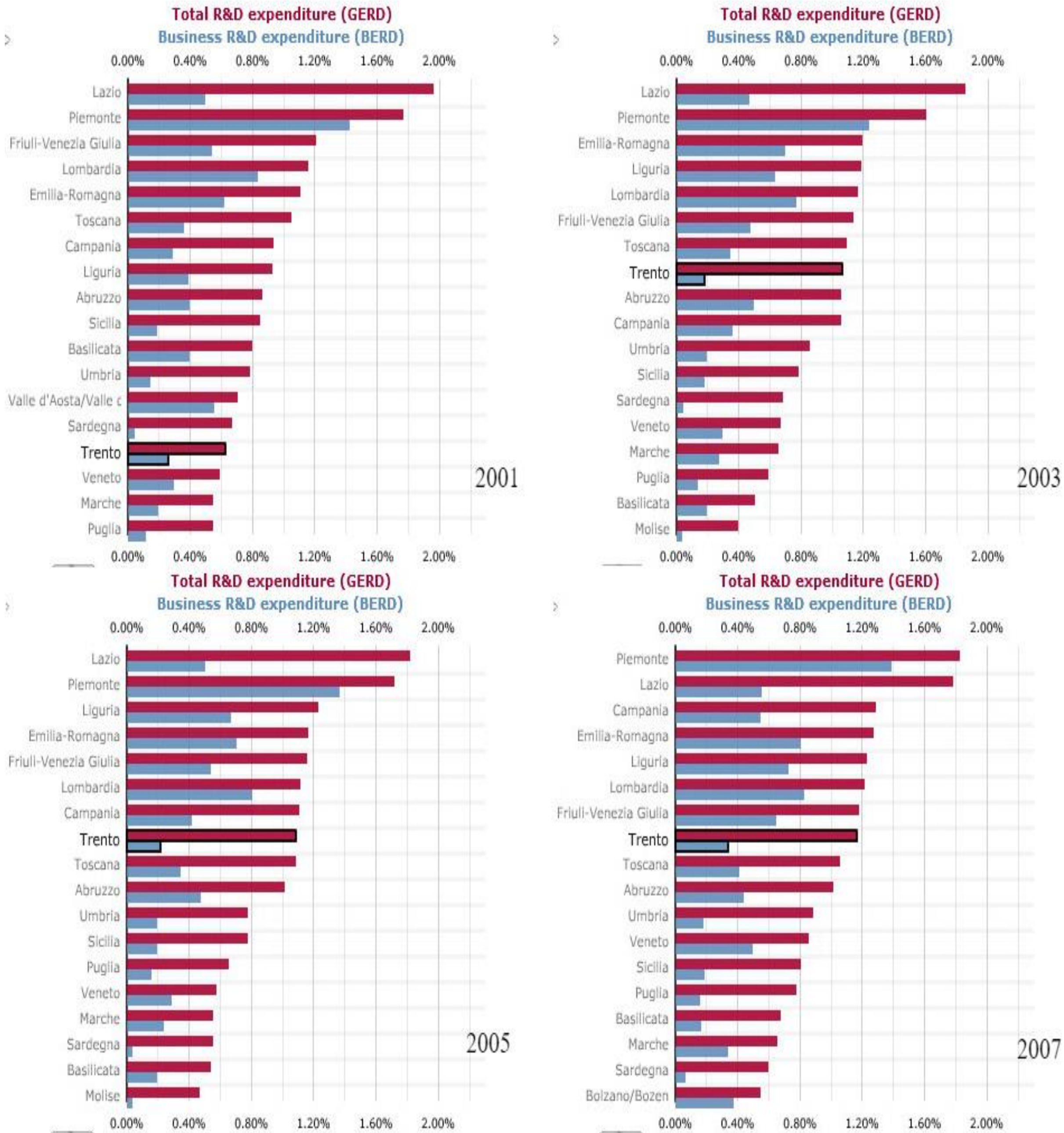

Figure 5. Regional total and business R&D expenditures for Italy, (2001,2003,2005 and 2007)

Source: ISTAT report 2014[25]

[25] ISTAT, Information and Communication Technologies (ICT) in Businesses. In Italian: Le tecnologie dell'informazione e della comunicazione nelle imprese, Comunicato stampa, 22 dicembre 2014.

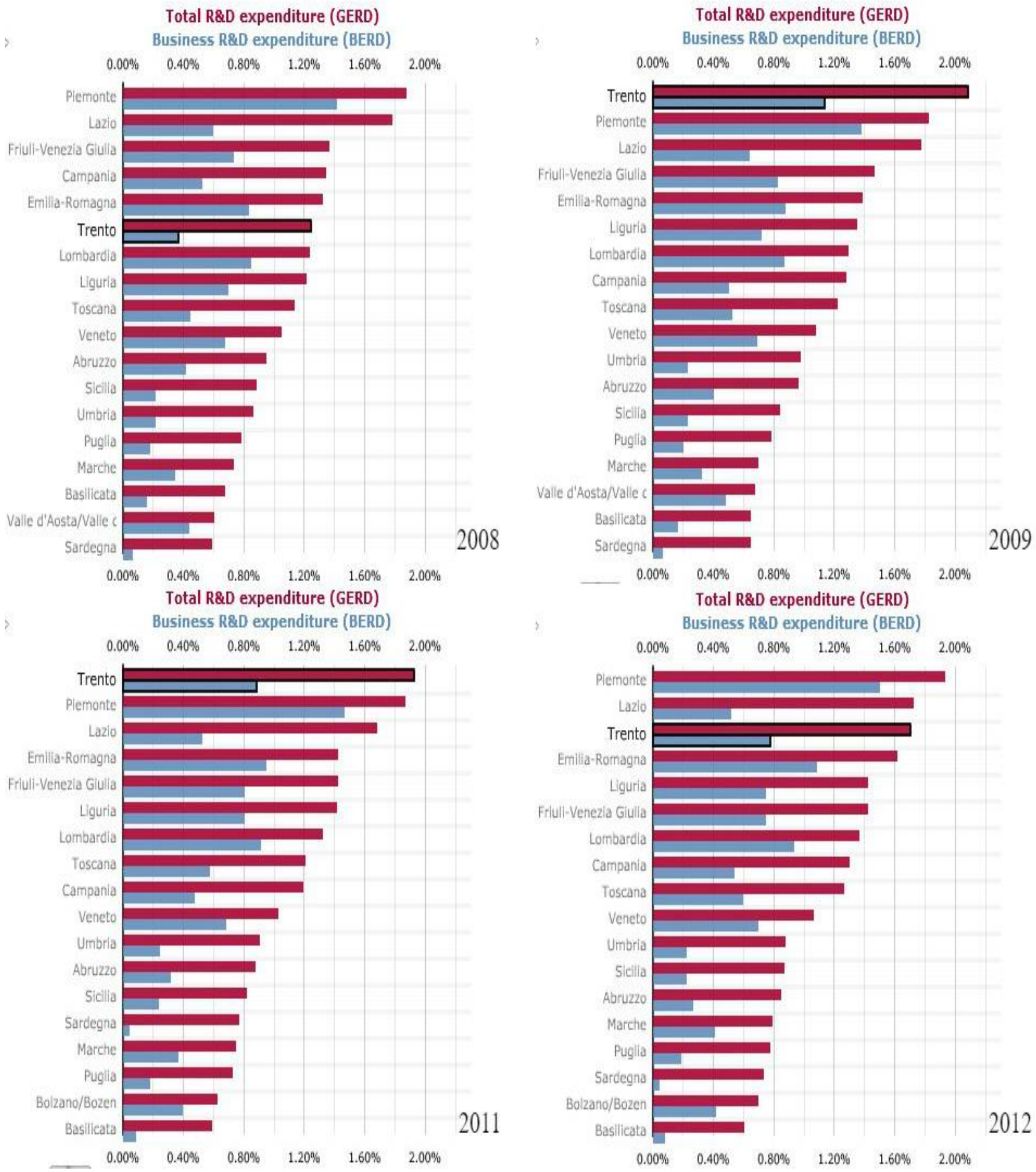

Figure 6. Regional total and business R&D expenditures in Italy, (2008, 2009, 2011 and 2012)

Source: ISTAT report 2014

The law and the R&D program will be described in detail in the following. Two years later, in 2003 the province experiences an amount higher than 1% for total R&D expenditures, while the share of private R&D expenditure is still very low in the total spending and even lower than 2001. The expenditures grow in 2005 with a GERD% amount around 1.1% and gradually higher in 2007.

Lazio and Piedmont (Piemonte) are the regions dominating on top of the list over this period, while changing their best and second-best positions in 2007 (first happening in 2006). Lazio and Piedmont regions have the highest amount of public total R&D expenditure and private R&D expenditure, respectively. The former has probably spent the most on R&D projects related to state, while the latter has spent the most on private R&D projects related to private industries and large private-owned manufacturing firms.

Figure (6) shows the dynamics of R&D expenditures for different regions for 2008, 2009, 2011 and 2012. Trento spends an amount slightly higher than 1.2% for GERD%, more than Lombardy (Lombardia) in 2008. In 2009, the amount grows incredibly to a ratio higher than 2%, putting up the region in the first place higher than Piedmont and Lazio. The business R&D expenditure enormously increases to an amount higher than 1% as well. To be more discussed in the next chapter, the province has introduced an agency responsible for allocating funds to R&D projects in the province just in 2009 in line with the law LP 6/99. Thus, this new setting and allocation of new budgets for R&D projects in the province can explain this sudden rapid increase.

Although the amount of the GERD% slightly decreases to 1.93% in 2011, however the province keeps on top of the list and consequently higher than Italian average of 1.25%. In 2012, The northern part of Italy still possesses the highest share of national R&D expenditure (60.6%). In terms of R&D public expenditures to GDP (at regional/provincial level), Trento province with a ratio of 1.71% remains among the best R&D performers after Piedmont (1.94%) and Lazio (1.73%) in 2012. For the private sector (excluding non-profit institutions), Trento stands after Piedmont (1.51%), Emilia Romagna (1.09%) and Lombardy (0.94%) as the three best performing regions. In Southern Italy, Campania shows the highest ratio between R&D expenditure and GDP (0.54%), while Calabria has the lowest (0.01%).

In a new ISTAT report for total R&D expenditures to GDP ratio (2016), the amount of GERD% for Trento province in 2012 is 1.8% leading as the second best performer (and not the third one) among other regions just after Piedmont.[26] Moreover, *the share of innovative enterprises in total number of enterprises* at national (for 2012) and regional level (the average of 2010-2012) have also been shown and discussed in detail in figure (1.b.1) and (1.b.2) in Appendix (1.b).

At this point, the indices for total R&D expenditure and private enterprise R&D expenditure with respect to total GDP for Italy and the Province of Trento have been spotted compared to other countries (specifically in EU28) and other Italian provinces for different recent years. This provides us a picture of R&D expenditure in the aggregate level in contrary to our study's firm level analysis. This picture helps us to understand what and where, the final effect of R&D policies and particularly the local-based R&D policy in our context would impact on. In line with Lisbon treaty's target of spending 3% of GDP on research and development investments, Trento province as an autonomous region in northern east Italy, has set objectives to increase investment in research and technology direct investment (RTDI) specifically for information and communication technologies (ICT) sector. These objectives include the support of small and medium sized enterprises in promoting their competitiveness, innovation and productivity.

A detailed description and review of the local-based R&D policy and the objectives it aims at, will be discussed in the following chapters. The public state and/or regional authorities set and apply different types of R&D policies to stimulate private R&D expenditures in order to finally increase the indices on R&D expenditure and input additionality. Next sections identifies and explains these different instruments and the evaluation of these different R&D policies.

3. R&D Policies

3.1 The economic importance of R&D policy

"Perhaps the most necessary thing that British institutions and after 1815 much of the western world contributed to the innovation progress was *what they 'did not do'* "; for instance not to highly tax the wealth of innovators to limit their venture capital which was vital for innovation. Therefore, innovators mainly relied on their own financial resources and private informal financial networks (Mokyr in Hall & Rosenberg, 2010). Centuries later, the modern government noticed not only it should stop deterring innovative activities, but also the state has the responsibility to

[26] This difference between data exists for some other years as well. The new data is provided based on the new available Istat website for data on science, technology and innovation.

encourage innovative activity for higher social welfare. However, innovation started to get supported by powerful institutional ties, access to the support of large investment banks and government guarantees and subsidies. At the same time, governments were mainly subsidizing research based on state priorities (Hall & Rosenberg, 2010).

Section 1, besides the importance of R&D and subsequently R&D policy for economic growth, discussed about how R&D policy aims to tackle underinvestment in private R&D due to the financial market failure and externality-induced reasons. Before reviewing the literature for R&D policy studies, this section develops the argument about the market failure for innovation (pointed out in section 1.3) and links it to the necessity for R&D policy to compensate the market gap. The idea is initially developed in articles by Nelson (1959) and Arrow (1962) following the work of Schumpeter (1942), the father of economics of innovation.

Knowledge as a basic resource for invention and making new goods or services, does not remain secret and is diffusible and nonrival. Hence, copy and imitation of a new invention (innovation) does not allow the inventor(s) to completely appropriate the returns to investment in knowledge. Therefore, the inventor (innovator) becomes reluctant to invest in innovation, which finally leads to R&D underinvestment in the economy.

In other words, risk and uncertainty in appropriation of the returns to R&D investment can make enterprises to carry out additional R&D activity lower than required for an optimal social return to R&D. In intellectual property right (IPR) literature, patents are known as a fundamental policy to encourage R&D activity by offering such a monopoly for the output of innovation activity carried out by the private firms (Barbieri et al., 2012). However, not only the input side of the innovation activity does not necessarily result in inventions or patents; but also large part of innovation output is not patented. Therefore, additional instruments such as monetary incentives for research and development are widely adopted by the social planner.

Even if problems with incomplete appropriability are solved using intellectual property right (IPR)[27], it can still be costly to finance R&D for a firm or an entrepreneur using capital from external sources. This can happen when there is a difference between the rate of return to R&D

[27] At the output level the appropriation of the R&D outcomes depend on the patent length (Nordhaus, 1969). There are theoretical analysis focusing on the optimal patent length as well.

investment required by an entrepreneur and that provided by an external investor which means the external finance for R&D might be more costly than internal finance. Reasons for this difference mentioned in the literature, are asymmetric information between inventors/entrepreneurs and venture capitalists, moral hazard generated by the entrepreneur because of ownership and management separation, and tax considerations (Hall & Lerner in Hall & Rosenberg, 2010).

Taking for granted that innovation activity and knowledge in all its forms play a crucial role in economic growth, therefore research on innovation policy as a part of science and technology and industrial policies becomes essential to provide literature and policy makers new insights about the issue. According to the discussion about market failure, innovation policy is required to "design legal methods of protecting innovations" (OECD, Oslo manual, 2005). The following section defines different types of R&D policies applied to encourage the private sector to spend more on R&D.

3.2 Different types of R&D policies

The line of reasoning provided in the previous section, justifies public policy interventions for increasing R&D activity by private firms. The R&D public policy appears in various forms, more frequently in form of government support for business R&D, R&D tax incentives and encouraging firms for cooperation in different types of research partnerships (R&D collaboration) and less frequently as award or prize system and procurement contracts. These policies are applied and implemented besides the current innovation protecting system or intellectual property system (for instance a patent protection system).

Becker (2015) categorizes the public R&D subsidies into three main forms, namely R&D tax credits and direct subsidies, support for university research system and training high skilled human capital and finally support for R&D cooperations across institutions. The first category, direct R&D grants and tax credits, represents the tools the government uses as the public finance solution for private R&D investment lower than social optimal amount.

The general features of research and development actors are universities and colleges, government labs and R&D intensive industries beside the federal states. The state make decisions on R&D investment and incentives. Investment decisions include funding for infrastructure for research (facilities and equipment), the development of human resources for business R&D and funding the research activities in labs and universities. Incentive decisions include encouraging the activities that stimulate economic growth through the use of knowledge, incentives for inventions in form of patents (a temporary monopoly claim), tax credits for increasing spending on R&D activities, support of small businesses' R&D projects and encouraging interaction between universities and industries in strategic areas (Shapira & Kuhlmann, 2003). This study's main focus is on direct R&D subsidies. In the following, first the award system and procurement mechanism are discussed. Afterwards, the discussion about main R&D stimulating policies will be developed and a review of the previous studies on R&D policy and the aspects these studies deal with will be provided.

3.2.1 R&D Award (Prizing)

A mechanism to encourage R&D is the award system. Design of an optimal award system to set the award size is difficult because the public authority must be knowledgeable about the feasibility of the inventions and the demand for the innovation. The award (prize) system has some drawbacks; the administrative body usually estimate the amount of the prize for innovation conservatively. Moreover, in contrast to the patent system the award system requires the innovator to transfer or define the knowledge or invention and to transmit the technological information to the decision maker which can be tricky. As long as the firms have more information about the market demand therefore, a less centralized solution like patent system functions better while there is also a correlation between the monopoly profits and the social value of an invention (Rockett in Hall & Rosenberg, 2010).

3.2.2 Procurement contracts or contractual mechanism

Procurement has features in common with award system, but there are major differences which makes this type of policy more widely used. In procurement, the government has control and access to the research market by signing more detailed contracts with a certain number of firms, while at the same time covering a part of the research costs. Excessive duplication of R&D projects would be avoided in this mechanism. Similar to the award system in which the agency must know the innovation value, in these types of contracts the government has information about the type of the project. This can be a reason why procurement policy is mostly used by space and defense projects (Edquist et al., 2000).

3.2.3 Tax Credits

Tax incentives beside the grants for R&D are widely used as a fiscal incentive and advantageous tax treatment in different forms to encourage higher R&D effort by private firms. Since 2015, 28 out of 34 OECD member states has provided tax treatments for business R&D expenditures (OECD, 2016).Tax credits can be divided into volume-based or incremental-based categories. The latter determines the tax relief on the total amount of R&D expenditure while the former is applied for the increased amount in R&D spending. In general the tax offset relates to the size or to the profit or loss making status of the firm (Wu, 2005) . Tax crediting is supposed to be more market oriented policy, as it let the private corporation to decide about the timing and amount of investment more flexibly (Klette et al., 2000).

R&D subsidies have a higher impact to increase R&D expenditures by private firms in medium or long-run term in contrast to tax incentives which affect the expenditures mainly in the short-run. Therefore, the tax credits have a quicker effect rather than direct subsidies for R&D (Guellec & Van Pottelsberghe de la Potterie, 2003). One interpretation can be that firms who use tax offsets in the market have already decided about the amount of R&D they carry out, while the firms being provided R&D subsidies have been selected by the government on a long-run aspect of their projects which may promote the firm to do more innovative activity at a later stage using their own internal funding. A study shows how direct subsidies and tax credits can be substitute for each other meaning that an increase in one may dampen the effect of the other in private R&D (David et al., 2000).

Furthermore, different internationally taxing regulations may lead to R&D mobility, and R&D in one country can be affected because of a change in tax credits in another country. This may further lead to foreign tax competition (Bloom & Griffith, 2001).

3.2.4 Incentives for collaborative R&D

Next strand of policies to encourage R&D activity is allocation of incentives for cooperation in R&D. Policy makers can facilitate R&D activity by industry linkages with national labs and universities. These linkages can be in the form of cooperative research and development relationships, interaction of companies and federal labs and university-industry relationships[28]. Collaborations can occur between knowledge exploiting organizations (firms and companies) and knowledge producing institutions (universities and research centers) or between the enterprise and its competitors (horizontal collaboration) and suppliers or customers (vertical collaboration or supply chain collaboration) (Fölster, 1995).

One form of cooperation in R&D is 'research joint ventures' (RJVs), which represents the agreements or contracts in which collaborating firms agree to share the costs and the profits of a research project (Marin & Siotis, 2008). There are similarities between RJV and licensing. They are both contractual mechanisms which may influence the R&D level at input or even output and the diffusion of innovation.

In contrast to appropriability problem which discourages firms to invest in R&D, business stealing effect may cause firms to spend higher than expected in R&D. The firm in a patent race increases its R&D effort in order to avoid the rival firms in the market to obtain the patent, leading to an overinvestment in R&D and duplication of R&D effort in the market. In addition to provide complementary use of other participants' assets, RJVs can help firms to cooperate and coordinate together to avoid and prevent the excessive duplication of similar R&D activities.

Promoting firms to participate in RJVs is considered as a policy to stimulate R&D especially when the patent protection system does not function effectively. The firms share the risk and uncertainty or the high fixed cost of conducting R&D individually, with other firms specifically when there is innovation spillover which makes the R&D-doing firms not to completely internalize the profits out of their R&D output. However, in the literature there have been evidence of RJVs leading to underinvestment in R&D when the collaborating firms may collude to avoid competition by the rivals in the research and development market (Cassiman, 2000; Shapira & Kuhlmann, 2003).

Growth of international collaboration programs (one evidence is the growth of international co-publication) and increased international mobility of researchers and scientists has led to globalization of science and industry. At the same time, this creates regional economy concerns

[28] University-led technology transfer, university linkage with economic development and movement of scientists and engineers are among university-industry relationships.

on labor market for researchers both about brain-drain and the methods to attract foreign researchers (Qiu & Tao, 1998).

3.2.5 R&D direct subsidies (grants or funds)

In public good argument a patent race winner might lose pay offs out of the new invention because of imitation by losers who free ride in the industry. This probably happen more often in industries with high spillovers. Spence (1984) suggests that government R&D subsidies can be a good substitute for a failing patent system (e.g. the innovation systems in developing countries with a weak IPR system).

As well as direct impact on additionality, the R&D subsidies can indirectly influence multiple potential variables together with R&D investment. The grant might convey signal on the profitability of the project and reduce the information asymmetries that subsidized firms face, leading to a lower private costs of capital (Meuleman & De Maeseneire, 2012). Moreover, by benefiting from the grants, firms may expand or upgrade their research facilities, train better their researchers, increase the revenue of other current or future projects, and eventually increase the marginal returns of the investment. These mechanisms can amplify the impact of the policy and induce firms to increase R&D outlays by even more than the amount of the grants (crowding-in).

In contrary, there can also be indirect effects acting in the opposite direction. Bronizini and Iachini (2014) describe a situation in which when the supply of the R&D inputs (such as researchers in a tight local labor market) is price inelastic and the subsidy program is sufficiently large, demand shift for inputs triggered by the public program might increase the costs, ultimately crowding out the subsidies.

Furthermore, subsidies can also impact the quality of the R&D activity. For instance, R&D subsidies can encourage a private firm to employ more scientifically skilled workers (e.g. by employing labour force holding PhD or M.Sc. degrees), which consequently may affect the quality of the project (Clausen, 2009).

Finally after reviewing different types of instruments used for stimulation of private R&D, the effectiveness of an incentive program is the main question of an evaluation study. In the following, we discuss the R&D policy (mainly subsidization policy) evaluation and the related literature and empirical works referred to the topic in the following sections.

4. R&D Policy Evaluation

When it is about policy, then policy evaluation comes after. Evaluation findings should effectively be linked with policy outcomes. In a world of complex innovation systems, evaluation plays a mediating role to inform and improve policy decision making. It is difficult to assess all benefits and costs of research and technology programs because of related spillovers, counterfactual explanations and learning effects. The policy design should also consider the new patterns of industry collaboration with growth of industry consortia, university-industry linkages, public-private partnerships and multinational research programs. The debate for public policy is how much government should invest in research, in what fields, under what conditions and with what economic and political goals. Annual monitoring of research provides us official indicators like number of published articles for academic research or number of patents for applied research. However, there are unobserved hidden impacts[29] and aspects of research which must be traced to have a comprehensive evaluation (Steinmuller, in Hall & Rosenberg, 2010).

The evaluation can be ex-ante (before program) or ex-post (after program) to demonstrate the value-added of a program[30]. Ex-ante evaluations evaluate plans before starting a program (policy). The ex-ante evaluation results are used to improve the plan and to judge the relevance of the program. Ex-post Evaluations verify whether the outcomes that the program (policy) aimed for are continuing after a certain period of time since the end of the program (JICA: Japan International Cooperation Agency, 2017). Positive evaluation of a program does not necessarily guarantee the program to pass political scrutiny, while at the same time negative evaluation of the program does not always lead to termination of the program. Mixed findings can happen in the evaluation particularly when there are multiple objectives or a change of objectives over time as stakeholders or political agenda change.

The main approach towards research policy evaluation and consequently the largest part of public R&D policy evaluation literature relate to the assessment of the effect of the policy on additionality. Evaluating the input additionality means investigation of how much extra the private enterprise spends on research with respect to the subsidy it receives. Measuring output

[29] Such as indirect effects of R&D policy discussed in section 3.2.5.
[30] Mid-term evaluation can also be considered as another evaluation method based on timing of the evaluation. Mid-term evaluation assesses the program while the program has already been implemented and is still being carried on. This study only deals with ex-post evaluation.

additionality evaluates what has been incrementally produced as a new production or produced by a new process as a result of public R&D funding. Behavioral additionality measurement is the last additionality effect evaluation which deals with the R&D activity the firm would have done even without the subsidy but in a different way (doing the research differently). For instance subsidies for R&D collaboration would motivate a firm to do the planned R&D project in cooperation with other institutions rather than doing it solely. The interpretations for additionality measurement can differ according to either the neoclassical or evolutionary approaches. Public R&D policy, in order to be effective on additionality must be capable to change firms' preferences and to push the firm to do the projects it would not have done without the public support (Bronzini et al., 2017).

The effectiveness of R&D support program depends on the success of the public agency to distinguish between marginal and inframarginal projects and provide the incentives to the former group (Lach, 2002). Subsidies should encourage the best unprofitable R&D projects to make the firm to carry out the project (Clausen, 2009). Public R&D subsidies are expected to trigger firms' investment in R&D projects which are marginally profitable. A project is marginally profitable when it would not have been undertaken without the public support. These projects are usually unprofitable if they get privately financed as their cost is higher than their rate of return. The impact of a successful effective public R&D support program on R&D expenditures and other interested target variables is realized by decreasing the cost of capital and increasing the investment profitability for marginal projects (Bronzini et al., 2014).

However, even assuming that the public agency performs quite well in selection of the firms to be subsidized, still the agency might not be totally capable of recognition of marginal projects. Furthermore, in order to be politically correct, the public authority concerned with public opinion can allocate the support to inframarginal projects with a higher probability of success (Lach, 2002). If a policy subsidizes the projects which are profitable even in the case of not receiving the subsidy (inframarginal projects), then the R&D support program would be ineffective. This happens because the firm will substitute the public grant with the private R&D investment to take advantage of the lower cost of the public funds. The effect of R&D incentives is usually studied through firm-level investment behavior due to the maximization of the profits by firms (Bronzini et al., 2014).

Furthermore, in a broader empirical point of view, the effect of R&D policy can be measured on other different target measures of interest (either theoretically or related the practical policy maker’s goals).The optimal policy to stimulate R&D even if we know whether there is underinvestment in science and technology or not, must be determined. In the following sections we review some of targeted variables of interest, besides additionality measures, which the effect of the policy on them has been empirically measured.

The challenges evaluation of complex research programs faces include intangible learning and network effects of research and fuzziness of objectives. In policy evaluation the scope of the evaluation, beside the direct effects of the policy should deal with the indirect effects of the policy as well. The direct effect is related to the main objective of the policy, while the indirect effect represents the factors which go beyond the objectives of the program. Indirect effects of the policy consist of technological effects (transfer of the new technology to other activities of the firm), commercial effects (the good image of doing research as a marketing tool), the organizational and methods effects and competence and training effects (the effect the innovation may have on human capital) (Shapira & Kuhlmann, 2003).

All in all, an ecumenical view to evaluation can help to choose the appropriate strategy for research evaluation. After second world war, the post evaluation of science and research did not seem to be necessary as there was an endless frontier approach to science, but the time for this approach has already passed. Now, the strategic mission-based research decision making brings the emergence for ex post evaluation of research programs to respect the social contract between science and the society due to the concerns about wealth creation, life quality improvement and policy relevance (Asheim et al., 2003).

Allison commission’s review of signal service in 1884 can be an evidence showing that evaluation of science and technology (S&T) programs is not a new concept. However, S&T programs evaluation hardly developed until the end of 1980s. The logic for why we need systematic science and technology program evaluations, can be referred to generic questioning of public sector to improve private sector allocation of resources, to consider opportunity cost of public expenditures, and to promote technology for citizens through public support for fundamental research. In addition, the evaluation is required to ensure the accountability of the agent in a principal-agent framework (Shapira & Kuhlmann, 2003).

Since early 80s, the European commission has set different waves of framework programs to evaluate R&D programs. Six frameworks have been introduced, while the importance of *socio-economic targets* has been emphasized in the last one leading to a redesign of the assessment mechanisms and related methods of data provision. The European approach towards R&D policy evaluation is bound up with national administrative culture. In Europe there are countries with centralized evaluation framework (like UK), countries in which the evaluation system is well established but still uncoordinated between ministries (like Germany and the Netherlands) and Nordic countries which the evaluation heavily uses the panelists. However, the European Research Area (ERA) concept has been developed to form a common understanding on science and technology policies and to integrate and develop the evaluation culture across Europe. One dimension of ERA is to identify the best practice in public policy and to spread the benchmarking policies for science and technology (Shapira & Kuhlmann, 2003).

In a local aspect, evaluating regional innovation is not simply as the national evaluation in a smaller scale. The European regions as innovation policy actors have been expected to follow the interactive model of innovation replacing the traditional linear model, to focus on SMEs as a specific target groups, to motivate innovation activity and dissemination of knowledge in the region and to promote proximity of regional actors in regional innovation system. The term "learning region" represent a region which monitors, measures and evaluates the research activity in the region and feedbacks the outcome of the policy evaluation to optimize future policies (Asheim et al., 2003). The question whether public R&D subsidies stimulate or substitute the private R&D expenditure is an empirical issue. Hence, the institutional settings and context differences can have an impact on the effect of subsidies on additional R&D spending (David et al., 2000).

5. Literature review of R&D Policy Evaluation

The first effort to evaluate R&D policies dates back to 1957 as Blank and Stigler investigated the relationship between public and private R&D in US, as the R&D budget had already raised much in 50s. As previously discussed, the literature for R&D policy evaluation mainly deals with studies measuring the effect of the policy on additional private R&D to investigate whether the policy has been effective in encouraging the business entity to increase its R&D activities or not. This section reviews the empirical studies in which the effect of R&D policy on R&D input and output and some other target outcomes have been measured. However, before literature review, we address the main challenges and issues R&D policy evaluation studies are exposed.

5.1 Challenges in Empirical Evaluation Studies

5.1.1 Selection bias and endogeneity problem in policy evaluation literature

Regarding the review of the works related to the effect of public R&D, one main issue in impact analysis of public subsidies is considering the selection bias which happens in non-random allocation of subsidies. *Firms' decision to apply for subsidies and the decision by public authorities to support R&D projects are not random* (Blanes & Busom, 2004). In a non-experimental setting, firms decide whether to apply for subsidies for R&D and public authorities perform a non-random selection based on their own criteria for assigning subsidies to firms to conduct private R&D (Kauko,1996). This makes the subsidies evaluation to be carried out only for a sample of firms whose applications to receive subsidies have been admitted, but not for the whole population of the firms. This mechanism causes endogenous subsidies allocation which leads to sample selection bias.

However, there are evaluation studies in which the impact of R&D subsidy programs has econometrically been measured, to investigate a causal relationship assuming that allocation of the subsidies by the public agency can take a *random pattern* (Griliches, 1986; Branstetter & Sakakibara, 1998; Griliches & Regev, 1998). If subsidies are allocated randomly, the data for supported and all non-supported firms can be analyzed using a quasi-experimental counterfactual setting. As long as there are many factors in political economy influencing the allocation, the evaluation results while treating the allocation as a random process can be valid and not misleading (Klette et al., 2000). However, in most cases the governments do not allocate funds randomly and select applications by firms based on some criteria or evaluation. Moreover, the firm previously self-selects to participate in the program based on some determinants.

As long as the R&D support given to firms, follows a selection process by the public agency, one can take R&D policy as a treatment to business enterprises. That means R&D subsidies are not allocated to firms randomly and the grants are assigned by decision and selection.[31] Therefore, not all firms in the non-supported sample have the same probability to be subsidized and this may lead to a bias in the difference between the performance of the treated versus non-treated firms and subsequently in the impact evaluated. At the same time, in the case unobservable firm characteristics impact the selection procedure, the subsidy variable is assumed to be correlated with the error term in an R&D equation. This will result in the bias in estimation of the effect of subsidies on the dependent variables (Clasuen, 2009).

The bias mainly arises when the unobservable term in the equations, identifying the impact of subsidy support on performance is correlated with support variable. To explain this, for instance if the public agency decides to support firms which perform inefficiently or to aid firms because of some uncontrollable shocks, or in reverse the government decides to pick winners and support firms with e.g. a high profit, all these may result in selection bias or generally the endogeneity problem.[32] The studies evaluating the impact of the policy, measure how the supported firms would have performed had they not been supported; that is, the difference in the outcome between supported and non-supported is the impact of the public policy. However, this difference can also stem from the fact that non-supported firms systematically perform differently, and this can be referred to selection bias. Accordingly, these studies dealing with policy impact evaluation have to use methods to remove this selection bias.

If the selection bias is not corrected, the analysis of policies and treatments may bring up misleading results (Czarnitzki et al., 2007). There are different methodologies to correct selection bias; those who benefit from a structural model like instrumental variable (IV) estimation, selection model (Heckit) first proposed by Heckman (1978) and control function which is based on the standard multiple regression analysis; and those who do not make functional form and statistical assumptions like difference-in-difference (DID) estimator and non-parametric method of matching. The most effective method depends on the available data, the characteristics of the database and R&D subsidy environment (Cerulli & Poti`, 2012). Cerulli (2010) reviews and discusses the econometric models measuring the effect of R&D public support on R&D

[31] Because the subsidies are not allocated randomly to the firms, the initial differences between subsidized and non-subsidized firms must be controlled (Clausen, 2009).

[32] In other words, there can be a 'picking the winner' or 'supporting the weaker' strategy in allocating R&D subsidies to the private firms. That means the public agency will not randomly assign subsidies to the firms eager to do R&D. This brings up the endogeneity and makes the subsidy variable endogenous, leading to biased results for policy evaluation.

investment. The models are described based on type of the policy (binary vs. continuous), the estimation method used (systems of equations vs. reduced form) and the type of data applied (cross-sectional versus longitudinal). The study continues with reviewing the main features of structural models and the important problem of endogeneity. Afterwards, the next generation of structural models (selection models) and their advantage in describing the two player (principal-agent) setting of the R&D incentive scheme are discussed. Subsequently, the more data driven empirical strategies analyzing R&D policy as a treatment are addressed. Control function and more in specific matching method are among these techniques. Afterwards, the study points out the evaluation methods using dynamic models of imperfect competition as the new strand of evaluation methods. In the following we make a brief review of different methods of innovation policy evaluation.[33]

According to Heckman (1978), sample selection bias can be viewed as omitted variable bias problem. The main Heckit model has been proposed by Heckman on wage level regressed on education. The problem arisen is that when data on wage and education is only available for those being employed. Consequently, the estimation of parameters to find out the relationship between education and wage would be biased without provision of the data for unemployed individuals. The same situation can occur for R&D output variables and subsidies. The data for R&D variables such as R&D expenditure or patents etc. are usually available only for the firms doing R&D. Therefore, the effort to measure the effect of R&D subsidies on R&D investment or R&D output will suffer from the selection bias if we cannot apply the data for the firms not doing R&D.

The IV estimation and selection model explain the interaction between public authorities' and firms' selection behavior within a system of equations. Endogeneity caused by selection on observable and unobservable factors can be tackled by these models. However, IV estimation requires additional information for instrumental variables, while the selection model assumes strong distributional hypotheses (Wallsten, 2000; Busom, 2000). For instance, Clausen (2009) used the total amount of funding in an industry (or the average subsidies in an industry) and also distance to R&D program as the instruments for the amount of subsidies in an Instrumental Variable (IV) setting to remove the endogeneity bias. Furthermore, the control function method

[33] We will briefly address the selection bias problem again in the next chapters (in other words and with brevity) to keep the cohesion and coherence of the chapter which is related to empirical evaluation of R&D subsidies.

uses a standard regression to identify treatment effects when the treatment is continuous (Florens et al., 2008).

Matching as a non-parametric estimation reduces the unsubsidized firms to a subsample of firms that are homogenous in characteristics with subsidized firms. A matching procedure finds untreated firms in a counterfactual state that are homogenous with treated firms with respect to a set of characteristics, in order to examine the effect of treatment (Almus and Czarnitzki, 2003; Pearl & Glymour, 2016). The usual method applied is for one unique treatment, but it has also been extended to evaluate the effects of multiple programs. As the advantage in contrary to previous estimators, matching is neither constrained to any functional form for the equations nor assumes a distribution on the error terms of the selection and outcome equations. The disadvantage is the technique only controls for observed homogeneity characteristics among treated and untreated firms, hence it will not be that reliable in case unobservable factors influence selection (Czarnitzki et al., 2007). The next chapters articulate matching technique and different types of matching procedures as the approach taken to tackle the bias problem and measure the average treatment effect.[34] Moreover, the reasoning and logic behind the choice for the methodologies will be explained in both following chapters.

Finally, difference-in-difference method can be applied when a longitudinal dataset is available. DID estimates average treatment effects (ATEs)[35] of panel data without any use of instrumental variables or assumption about the distribution of unobservable characteristics (Lach, 2002). If there is the possibility to combine DID with matching procedure, the mix provides an additional advantage to matching method; i.e. removing the probable bias of correlation between unobservables and firms' investment without the need for instrumental variables or statistical distributional hypotheses. However, the drawback of the method is the need to an enriched longitudinal dataset embracing a long period of non-missing data for all observations. If this condition strongly holds, there is even the possibility to go beyond and use difference-in-difference-in-difference together with matching which adds the capability to investigate multiple

[34] In addition, the average treatment effect (ATE) and the average treatment effect on treated (ATET) will be discussed more in detail through next chapters. Chapter 4 provides a description on structural model approach towards treatment effect analysis as well.

[35] The average treatment effect on treated and the whole sample will be discussed in detail through Chapter 3.

treatments (subsidies program) to the options and properties of DID (or DD) (e.g. the study by Barbieri et al. (2012)).

Instrumental variable(IV) method (Busom, 2000; Wallsten, 2000, Clausen, 2009); control function (Florens et al., 2008); Difference-In-Difference (Lach, 2002; Marino et al., 2016); Regression Discontinuity (RD) method (De Blasio et al., 2009; Bronzini et al., 2014; Cerqua and Pellegrini, 2014; Wang et al., 2015, Bronzini & Piselli, 2016; Dechezlepretre et al., 2016), two-stage econometric model (Bannò and Piscitello, 2010), matching techniques[36] (mainly nearest neighbor propensity score matching) (Atzeni and Carboni, 2008; Gonza´lez and Pazo, 2008; Czarnitzki et al., 2011; Guerzoni & Raiteri, 2015; Hud and Hussinger; 2015,) structural modelling (Takalo et al., 2013), and mixed-methodologies like Matching DID (MDID) (Bernini and Pellegrini, 2011) are among the various studies coped with the selection bias challenge. Propensity score matching procedure which is the methodology used in this paper, will be discussed more in detail in the following chapters.

The robustness of these econometric models other than IV estimation has been examined regarded to the choice of target variables in the study by Cerulli and Poti`(2012). When target variables are expressed as ratios (such as R&D intensity and R&D per employee), all the methods that they investigated were significantly robust. However, when R&D expenditure is taken as the target variable, there is a strong variability between analysis methods.

5.1.2 Multiple treatment (Co-presence of Incentives)

In empirical policy evaluation, when the researchers investigate the effect of one specific public policy, there is a possibility that firms receive grants or support from more than one incentive program. This case particularly occurs when there is no restriction on benefiting from a single source of public support for the applicants. In situations where the firm can take advantage of applying for regional and local subsidies, beside national (or EU) subsidies, the impacts of two policies might intervene and mix up. Subsequently, there arise the problem of distinguishing the pure effect of a single program for the sake of monitoring indices for policy makers. However, in

[36] Including propensity score matching (PSM), Nearest neighbor(s) matching, Kernel matching and Radius matching which will be defined in the following chapter.

many cases the public agency regulates the law to allocate funds not allowing for an overlap in public support policies.

The idea can be better clarified with a simple example. Assume there are two incentive policy programs; let us call them A and B, that the firm is benefiting from. Policy A has the effect X while policy B has the effect Y. Assuming of no overlap between policies, the global impact of policies A and B, has to be $X + Y$. However, the total impact is usually less due to the overlap and substitution of the policies. In some cases, the effect can be even higher than the sum of the effects due to behavioral additionality and learning effect. This can happen when the agent learns from policy A, hence she can gain more from policy B. In rare cases, the impact can get less than X because of severe distortions in the system of policies.

In the empirical literature Barbieri et al. (2012) study the effect of Italian law 46/82 and its revisions on R&D expenditures and R&D employment generation. The research considers the overlap of different state policies on the firms in different categories. Law 46/82 has been the main public instrument to regulate incentive programs to support R&D and innovation of Italian firms. The authors use DDD (difference in difference in difference: referring to Wooldridge (2007) and Imbens & Wooldridge (2009)), to distinguish and realize the impact of different simultaneous incentives. The DDD estimator adds a term in the regression equation which captures the effect of the multiplication of policies to investigate the effect of the co presence of policies. The results in this case suggest the existence of some inefficiency in overlapping the instruments for R&D stimulation. Nevertheless, this technique demands a rich panel or longitudinal dataset which cover a quite long period of analysis.

Moreover, Guerzoni and Raiteri (2015), estimate the impact of three different R&D policies functioning together in the same context. They cope with this issue of multiple (hidden) treatment by applying 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 (3 policies and 10 combinations).

5.1.3 Time span

Turning into the review of the findings of net impact evaluation for public R&D, studies may deal with short-run and long-run effects. A limitation in many studies is that they analyze mainly the short-term effect of the subsidies. Hence, using a panel data analysis like the one in our study provides the effects over a long run which can show whether the effects of the support through a longer time span is the same as short run effects. In addition, The effects measured are likely to be ambiguous and mixed between complementarity and crowding out according to literature review. The direction and magnitude of short-run or static effect is almost evaluated without consideration of long-run or dynamic effect stemming from knowledge spillovers and training new scientists and engineers in the long run (David et al., 2000).

5.1.4 Mixed heterogenous findings and lack of result conclusiveness

Dimos and Pugh (2016) in a meta-regression analysis of 52 micro-level evaluation studies, published after the David, Hall and Toole's 2000 paper, reject crowding out of private investment by public subsidy but without any substantial additional effect for the subsidies. However, they come to the conclusion of inconclusiveness of the effect direction in evaluation studies.

More than a decade before, as one of the most cited references in R&D policy evaluation, David, Hall and Toole (2000) have also reviewed the literature of empirical papers over past 35 years before 2000, in which the net effect of public R&D (government subsidies) on private R&D have been evaluated at laboratory, firm, industry and aggregate levels. The studies investigating the literature answer to the question whether the public R&D complements (is additional to) or substitutes (crowds out) the private R&D using the time series or cross-section data. They analyzed 33 studies in all levels of aggregation investigating the relationship between public R&D (subsidies) and the private R&D. Eleven of these studies were showing the crowding out effect, while others had a different conclusion. They suggested that the heterogenous findings can be because of the tendency of these papers to eschew a structural model in the policy evaluation. This leads to lack of specifications in evaluations' econometric analysis and ambiguity and uncertainty in interpretation of each individual research findings and evidence. They propose setting out a conceptual framework which identifies the micro-level determinants of private R&D investment and is capable of linking these determinants to a macro-level setting.

However, the empirical literature even years after David et al.' s study still believes in mixed findings and results of the effect of R&D policies on innovative activity and other growth measures (Caloffi et al., 2016)[37]. At the same time, Bernini et al. (2017) notice that the investment subsidies including R&D subsidies evaluation literature is very versatile in terms of the estimated impact of the subsidies which according to (Brandsma et al., 2013) reflects differences in the institutional context between countries, regions, sectors and firms, differences in the design of the policy and policy implication mechanisms and differences in the quality of data and the analytical method used in the empirical studies. There are studies showing that public R&D subsidies stimulate R&D expenditures and innovation output by private firms (Levin & Reiss, 1984; Klette & Moen, 1998; Busom, 1999; Czarnitzki & Fier, 2002; Almus & Czarnitzki, 2003; Heshmati & Lööf, 2005, Hall & Bagchi-Sen, 2007, Block & Keller, 2008); while on the other side, there are articles finding a crowding out or R&D substitution effect, i.e. a negative impact of policy on private R&D (Wallsten, 1999; Lach, 2002; De Jorge & Suarez, 2011). Moreover, Some other studies conclude there is not such a clear evidence if public funding positively affects higher R&D spending (Lichtenberg, 1987; Kauko, 1996), while a few found significant effect but both positive and negative mixed based on different research settings related to the target variable[38], time effect etc. (Fölster, 1995; Clausen, 2009). Therefore, The effects measured are likely to be ambiguous and mixed between complementarity and crowding out regarded to the literature. In their taxonomy, David et al. (2000) have categorized previous studies on impact evaluation of public subsidy on private R&D based on the levels of analysis. They discuss the net effect findings of each study under a specific categorization to see if there is complementarity or substitutability effect. They conclude that the findings are heterogeneous and mixed.

On the other hand, the evolutionary approach towards the R&D policy focuses on the reasons behind the different behavior of the firms which can lead to this heterogeneity of the effects. Evolutionary approach takes the firm, as well as the public agency, as complex entities which adapt to the changing environment with uncertainty, asymmetric and bounded rationality. The dynamic changes of the environment make firms' choices diverged. Hence, the firms' capacity

[37] Caloffi et al. (2016) in their working paper review 43 studies related to the micro-economic evaluations of innovation policies in Italy using a meta regression analysis. They find out that most of the program evaluations show positive probability of success. In addition, the probability of success is higher for the regional governments.

[38] For instance Basic research vs. applied research, or Research vs. Development (Clausen, 2009), and results sharing vs. non-result sharing (Fölster, 1999).

to accumulate knowledge and to learn by interacting to other actors are addressed in this approach. In other words, the evolutionary approach deals with opening up the black box to show how the policy may impact a firm as an agent. At the same time, the idea of 'best policy' or the 'optimal instrument' does not hold in this approach.

Concentrating more into firms' responses to policy, Barbieri et al. (2012) while measuring the average treatment effect on the treated (ATET), capture the average effect of the policy on the target variable on the whole sample of different beneficiary firms. However, they admit the response of these firms to the policy can be heterogenous with very divers positive or negative effects.

Evaluation methods and research on measurement of the net or overall causal effect of R&D incentives, without a framework, do not describe the mechanisms through which the incentives probably make an impact on R&D expenditures, and solely concern the magnitude and the sign of the effect. On the other hand, evaluation methods using a framework or analytical model get restricted to a theoretical model based on the mainstream trend in industrial organization to show inside the black box in which the subsidy policy affect the R&D investment by the firms. Evaluation studies should consider the individual firm's determinants of investment behavior in innovation.[39] If one study does not involve micro-level analysis then the findings of the econometric analysis will be only a magnitude of net effect at the macro-level with a specific direction of effect (positive or negative) disregarded of the channels which relates the evidence of the experiment to individual firm's determinants (David et al., 2000).

In this line and to deal with the heterogenous response problem (firms probable heterogenous responses to R&D policy), Sissoko (2011) suggests to categorize firms based on the distance to technology frontier. He believes firms far from the frontier are more likely to benefit from R&D support.

A considerable part of the investment subsidies evaluation refers to R&D subsidies evaluation. However, almost the whole literature has focused on the effect of the public subsidies on R&D input or output additionality. There could be found few studies in which they have evaluated the impact of the public capital investment subsidies on TFP. Furthermore, even fewer

[39] This study takes into account both approaches in R&D policy evaluation.

number of studies have focused on the impact of the R&D subsidization policy on TFP (Bernini et al., 2017). The next section reviews some of these studies in brief and Chapter 2 extends this review.

5.2 The literature of the effect evaluation of R&D policy on targeted outcome

There is a large literature in policy impact evaluation dealing with the effect of investment incentives on additional investment or some other outcome measures. Investment can be categorized as capital investment, investment in human resource, investment in restructuring, research and development investment and etc. One main share of this literature links to the studies investigating R&D incentives' effect.

As noted previously, a main classical study referred for a review of evaluation studies has been carried out by David, Hall and Toole (2000). More updated, the meta-regression study by Dimos and Pugh (2016) has covered and included various international empirical studies (52 papers for 28 countries). The interested reader can easily access to the details of these studies based on sample period, observations, type of data, estimation method, type of R&D outcome (input or output), measure of treatment and the results. At the same time, Caloffi et al. (2016) are working on a paper applying a similar methodology on a taxonomy regarded the Italian context (43 different articles).

Empirical research has mainly been focused on evaluating the effect of R&D incentive on input additionality. One main reason is that measuring R&D spending is more straightforward in comparison with innovation performance. The first step in evaluation studies is to investigate if the public policy has a substitution or a complementarity effect on R&D input, using cross sectional data, time series or panel data. The analysis is performed at country (aggregate), industry or private firm levels. However, the effect measured for private firms is less homogenous because of applying different estimators or approaches in different specific contexts where the policy is adopted.

The methodologies used, as discussed in the previous sub-section, mainly follow a quasi-experimental approach. Multiple regression equations, matching methods and instrumental variable (IV) method being discussed in the previous section can be used dependent to the type of available data and bias the study deals with. The econometric results are ambivalent and there are various studies concluding the impact to be either additionality or crowding out as well as studies which do not yield any significant result (Garcia-Quevedo, 2004).

As an empirical analysis of this thesis relates to the effect of R&D program on productivity change, in the following and partially in the next chapter, the review is also extended to studies with different targeted variables than additionalities, specifically TFP change. In the next sub-sections, we review some literature related to the effect of the R&D policy (in particular R&D subsidies) on additionality measures. Afterwards and also in the related chapter, the studies explaining a dependent outcome variable different from additionalities will be addressed. The review will point out different aspects of these policy evaluation studies, such as treatment, target and control variables used, methodologies implemented, data applied and the effect of the policy on targeted outcome.

5.2.1 Studies related to R&D policy impact evaluation on R&D input additionality

In the following some evaluation studies, related to our study, which have measured the effect of the R&D policy on input additionality will be briefly reviewed. In addition, table (1) will then provide a review of some other related studies. Atzeni and Carboni (2008) have used the *nearest neighbor matching estimation* to measure the average treatment effect of public grants on ICT adoption in terms of ICT investment in Italy considering the regional disparities between the south and the north in technological indicators. The non-parametric estimation is carried out for two waves of data for the periods 1998-2000 and 2001-2003. The difference of their methodology with the propensity score matching is that there is no need for covariates to determine the probability of being treated and the estimator takes into account only the characteristics influencing ICT investment.

Bronzini et al. (2014) assess the impact of a unique local R&D program in Emiglia-Romagna region in northern Italy using a sharp regression discontinuity (RD) method well suited with the mechanism of direct R&D subsidies allocation. The policy's local dimension allows for the removal of unobserved heterogeneity among private firms in comparison with the R&D programs nationwide in which the recipients and non-recipients are less similar.

Guerzoni and Raiteri (2015) review and discuss the effect of different various technological policies upon firm's innovative behavior proxied by the change of spending on all the firm's innovative activity. They discuss the effect and interaction of R&D subsidies and R&D tax credits as supply-side innovation policies and the public procurement as demand-side R&D policy. They find out that public procurement can be even more effective on innovative behavior. They use different matching methods to estimate the impact of all different possible combinations of treatments (3 main treatments i.e. 10 different treatment indicators) on R&D spending increase as the outcome indicator. They choose age, size and the market which firm operates in as control variables.

Marino et al. (2016) have measured the impact of R&D subsidies and R&D tax credits on private R&D expenditures for a sample of French firms during the period 1993_2009. They investigate the impact on input additionality (crowding-in) or substitution (crowding-out) of the subsidies using difference-in-difference and propensity score matching combined. The effect of R&D support has been assessed between differently treated firms as well, based on a dose-response (continuous treatment variable) matching method to identify the optimality of the R&D support provision.

Czarnitzki and Delanote (2017) have integrated the R&D subsidy into the famous structural model of CDM[40] to link the policy to both innovation input and output. They investigate the classical questions of input and output additionalities, but this time in an integrated model in which the R&D subsidies is given in a selective mechanisms to admitted applicants. They use simple dummy variable approach for the subsidy variable and separate R&D input from subsidized amount in regression equations. They find out input additionality for public funds and positive output effect for both privately and public subsidy-induced R&D investment. However, the study lacks the assumptions for R&D spillovers. The main focus of the literature has been evaluation of input additionality, however, some studies have also dealt with the output additionality. This output additionality is the factor leading to productivity growth.

[40] Crépon, Duguet and Mairesse (1998) proposed a model of R&D, innovation and productivity known as CDM model identifying how R&D effort explains innovation and how innovation determines productivity. CDM model will be defined more in the following chapter.

5.2.2 Studies related to R&D policy impact evaluation on R&D output additionality

This sub section reviews some evaluation studies related to our study, which have measured the effect of the R&D policy on output additionality. As the last paper of Czarnitzki and Delanote (2017) pointed out in previous section, which deals with output side of R&D process (together with input additionality effect); some other studies put their concentration on impacts of *R&D incentive* on innovation output. However, the proportion of these studies is still lower than those measuring effect on input additionality for the reasons mentioned in the last section. The most common proxy for innovation output is number of patents. However, as discussed previously, not all inventions turn to be registered patents and not all innovation activities carried out lead to patents. In the following we point out some studies related to measurement of output effect.

Czarnitzki and Hussinger (2004), Czarnitzki and Licht(2006), Hussinger (2008) and Czarnitzki and Delanote (2015) for example, use the estimated private and treatment effect obtained from a matching estimator or selection model in an output equation, in order to measure the effect of private and public R&D on innovation output. However, these studies use more reduced-form-type models rather than incorporating R&D subsidy variables into a more structural approach. Furthermore, Bronzini and Piselli (2016) evaluate the effect of a placed based R&D subsidies program on innovation output proxied by patent application and the probability of patent application by subsidized firms using regression discontinuity design. They realize that the program has been positively affecting the number of patent applications especially for the smaller firms. In addition, they find out that the R&D subsidies influence positively the likelihood of application for patents only for small firms. This happens mainly because SMEs suffer more from financial friction (Hall & Lerner, 2009).

In most empirical studies the effect of R&D incentives has been evaluated on R&D input (R&D expenditure) rather than innovation itself. However, there are some countable studies managing with the impact evaluation of R&D incentives on innovation output (output additionality) as some were reviewed just above. In the following, table (1) reviews some studies related to the measurement of the effect of R&D policy on mainly input and also output additionalities in a chronological order .

Table 1. Studies related to impact of public policy on private R&D expenditure (input additionality) and R&D output (patent)

Study	*Dataset*	*Level of Aggregation*	*Period*	*Observations*	*R&D Policy Variable*	*The Target Variable*	*Control Variables*	*Evaluation Methodology*	*The Effect*	*Notes*
Levin and Reiss (1984)	*Panel*	*Industry Level*	*1963,1967 1972*	*60*	*Government R&D*	*Private R&D*	*Technological dummies, basic research share, Industry age, Market concentration index*	*2SLS*	*Significant (+)*	*Complementarity*
Lichtenberg (1987)	*Time series*	*Aggregate (Country) Level*	*1956-1983*	*28*	*Public contracts with industries*	*Private R&D Expenditure*	*Sales to government*	*OLS*	*Insignificant*	*—*
Klette and Moen (1998)	*Panel Data*	*Industry Level*	*1982-1995*	*192*	*Subsidy Log*	*Private R&D Log*	*Sales, Sales sq., Cash flow, time dummies*	*Fixed Effect OLS*	*Significant (+)*	*The case of Norway, Complementarity with elasticity 0.06*
Busom (1999)	*Cross Section*	*Firms across Industry*	*1988*	*147*	*Participation in Subsidy Loan Program*	*Private R&D Expenditure*	*Size, Patent, Export share, Industry Dummy*	*OLS with selection correction*	*Significant (+)*	*Complementarity (0.2)*
Wallsten (1999)	*Cross Section*	*Firms across Industry*	*1990-1992*	*81*	*Number of SBIR award, Total value of SBIR awards*	*Private R&D in 1992*	*Age, Size, Patents, R&D exp. (1990), Industry and Geography Dummy*	*OLS, 3SLS*	*Significant (-)*	*Substitutability*
Lach (2002)	*Panel*	*Firm Level*	*1991-1995*	*325*	*Subsidy (t and t-1)*	*R&D Expenditure*	*Employment industry dummies time dummies*	*Difference-In-Difference (DID)*	*Significant (-)*	*The mixed effect dependent to subsidy time and the size of the firm*
Gonza´lez and Pazo (2008)	*Panel*	*Cross country at firm level*	*1990-1999*	*9455 observations of 2214 firms*	*Public R&D Subsidies*	*Private R&D*	*Size, capital growth, age, indicator for using advanced technology*	*Matching approach (propensity score matching)*	*Significant for small low-tech industries*	*No crowding out effect either partial or full*
Clausen[41] (2009)	*Panel*	*Firm Level*	*1999-2001*	*1074*	*'Research' and 'Development' (R&D) Subsidies*	*Private R&D*	*Size, Age, Group, Foreign Ownership, Export Intensity, Patent, Industry*	*2SLS Regression*	*Significant (+/-)*	*R subsidies +, D subsidies -*

[41] Clausen (2009) distinguishes between subsidies allocated for "research" and "development" in his study that examine the positive impact of subsidies on innovation activity in Norway. The results of this study show that "research" subsidies stimulate R&D expenditures, while "development" subsidies substitute such spending. These results are consistent with the argument that the gap between social and private rates of return is higher for basic research than for development projects (Nelson, 1959). This difference in research projects versus development projects is worth to pay attention as the authority in our context sets subsidies amount with respect to the nature of the projects which are categorized in two sorts of industrial research or experimental research.

Cerulli and Poti` (2012)	*Panel*	*Firm Level*	*1998-2000, 2002-2004*	*5923 for both period*	*Public R&D Subsidies*	*Business R&D*	_	*Robustness Check (Heckman selection model), Control function, Difference-In-Difference(DID), Matching Methods)*	*Significant*	*Absence of full crowding out effect, Robust results for the effect on R&D intensity and R&D per employee but variable results for R&D expenditure between different approaches*
Takalo et al. (2011)	*Panel*	*Firm (project) Level*	*1999-2002*	*14,657 firm data, 914 Applications for subsidies*	*Public R&D Subsidies*	*R&D expenditure, Expected Spillover (Social welfare variable: social rate of return)*	*Age, Size, Sales/Employee, Parent company, Number of previous applications, Exporter dummy, Board size*	*Structural Model (Econometric estimation of a game-theoretic structural model)*	*Significant (Heterogenous)*	*Subsidized firms internalize on average 60% of the total effect*
Klette and Moen (2012)	*Panel*	*Business Unit Level*	*1982-1995, 2001-2007*	*697*	*R&D subsidies*	*Private R&D (Additionality)*	*Sales, Technological opportunity, Appropriability degree*	*Fixed Effect OLS*	*Insignificant for first period, Significant (+) for the second period*	*A pre-2000 post-2000 comparison of the effectiveness of the policy for Norwegian firms*
Bronzini and Iachini (2014)	*Panel*	*Firm level*	*2004-2005*	*254 treated vs. 103 untreated*	*Regional program L 7/2002 in Emilia-Romagna region in Italy*	*Total investment, labour cost and service cost / pre-treatment sales*	*Size, Sector (manufacturing or service), Age, financial vulnerability*	*Sharp regression discontinuity design*	*Positive (+) impact for the whole sample but heterogenous impact for different categorizations*	*The paper has been published in American Economic Journal, 2014; Critical choice for proxies related to R&D investment*
Czarnitzki et al. (2007)	*Panel*	*Firm level*	*1994-1996 1998-2000*	*1,464 (1,520) German (Finnish) companies*	*R&D subsidies and collaboration (as treatment)*	***Patent activity and R&D expenditure***	*Size, Export, Group, Appropriability conditions*	*nearest-neighbor matching and difference-in-difference*	*No effect for Germany/ Positive effect for Finland*	*The context of the "Action Plan 2010" by the European Council*
Bronzini and Piselli (2016)	*Panel*	*Firm level*	*2004-2005*	*379 treated vs. 178 non-treated*	*Regional program L 7/2002 in Emilia-Romagna region in Italy*	***Patent applications & likelihood of submissions***	*Size, Sector, some financial statement sheet items*	*Regression discontinuity design and difference-in-difference*	*Positive(+) impact on patent applications mainly for smaller firms*	*The additional patent application demands grants between €206,000 to €310,000*

5.2.3 Studies related to R&D policy impact evaluation on R&D behavioral additionality

The literature related to empirical evaluation of R&D subsidies effect on behavioral additionality is scant.[42] However, a part of the attention has been recently tended to the aspects related to the effect of R&D subsidies on behavioral additionality. Hsu et al. (2009) have evaluated the effect of R&D programs on behavioral additionality, beside input and output additionality. Their empirical investigation demonstrates that behavioral additionality of recipient firms could be classified into project enlargement, strategy formulation, cost-effectiveness, and commercialization behavior. Their results show that firms in different industry sectors and innovation categories emphasize different additionality, respectively.

Wanzenböck et al. (2013) have focused on three different forms of behavioral additionality-project additionality, scale additionality and cooperation additionality and found out R&D related firm characteristics significantly affect the realization of behavioral additionality. They studied 155 firms supported by the Austrian R&D funding scheme in the field of intelligent transport systems in 2006. Autio et al. (2008) in terms of second-order additionality and Busom and Fernandez-Ribas (2008) in terms of R&D partnership have also dealt with this type of additionality in their studies.

5.2.4 Studies related to R&D policy impact evaluation on target outcomes different from additionality

The targeted dependent variable in empirical evaluation studies can differ from additionality. A diverse strand of the literature refers to measurement of the effect of R&D policy on other outcome indices different from different types of additionality. These indices mainly regard economic growth and proxy the endogenous growth at micro and macro levels. One main target variable representing a relatively comprehensive measure for economic growth is TFP and TFP change. Next chapter will review and discuss the studies dealing with total factor productivity or other related measures as the outcome variable.

However, beside productivity, there are also other various dependent targeted variables different from R&D additionality such as technology adoption (Atzeni & Carboni, 2008);

[42] A search in papers published after 2007 with R&D behavioural (behavioral) additionality in title, abstract or keywords, provides only 5 related articles.

spillovers (Takalo et al., 2013); innovative productivity and follow-on funding (Howell, 2014; Zhao & Ziedonis, 2014); employment, capital investment and turn over (Cerqua & Pellegrini, 2014); internationalization (FDI) and performance in terms of turnover (Banno` et al., 2014); survival (Howell, 2014; Zhao & Ziedonis, 2014; Wang et al., 2015) and patenting and new investment(s) (Wang et al., 2015). Table (2) in the following will review some other related papers which have measured the impact of R&D policy on these outcome measures.

6. Remarks

Hereby, the chapter has comprehensively addressed the theoretical and empirical issues concerned with R&D policy specifically R&D public subsidies. The relationship between R&D activities and the economic growth, beside the neoclassical market failure leading to underinvestment in private business R&D, oblige the policy maker to act as a benevolent social planner in maximization of social welfare by an optimum (or sufficiently good in a different approach) design of mechanisms to incentivize private R&D activities. This mechanism or program theoretically focuses on maximizing spillover effect in terms of positive externalities of R&D projects carried out by enterprises. All these elements of an R&D policy have been discussed and defined in previous sections, beside a practical review of R&D expenditure measures at different levels of analysis. In addition, the theoretical and empirical aspects of R&D subsidies and a detailed literature review have been provided. Now at this point, the substantial concerns and challenges to be addressed in empirical evaluation of a specific R&D program (at national, regional or local level) have been determined.

Through next chapters we apply materials provided and issues covered in this chapter beside other related topics and the topics linked to each chapter, in order to empirically measure the effects of a placed-base R&D subsidy policy using constructed datasets. However, before continuing with the applied and empirical estimations regarding the R&D subsidization policy evaluation, in the next chapter we provide an introduction and develop the literature about the effect of R&D policy specifically public R&D subsidies on TFP change. Applying that new literature beside current chapter's literature review about the effect of R&D subsidies on additional R&D expenditure and the discussions related to main challenges R&D policy evaluation face, we frame our research hypotheses to be empirically investigated.

Table 2. Studies related to the measurement of the effect of R&D policy on target variables different from R&D additionality

Study	*Dataset*	*Level of Aggregation*	*Period*	*Observations*	*R&D Policy Variable*	*The Target Variable*	*Control Variables*	*Evaluation Methodology*	*The Effect*	*Notes*
Czarnitzki et al. (2011)	*Cross Sectional*	*Firm Level*	*1997-1999*	*3562*	*R&D tax credits*	*Doing R&D Decision*	*Size, Firm's innovation behavior, Industry*	*Non-parametric Matching*	*Significant (+)*	*Canadian firms*
Takalo et al. (2011)	*Panel*	*Firm (project) Level*	*1999-2002*	*14,657 firm data, 914 Applications for subsidies*	*Public R&D Subsidies*	*, Expected Spillover (Social welfare variable: social rate of return)*	*Age, Size, Sales/Employee, Parent company, Number of previous applications, Exporter dummy, Board size*	*Structural Model (Econometric estimation of a game-theoretic structural model)*	*Significant (Heterogenous)*	*Subsidized firms internalize on average 60% of the total effect*
Bann`o et al. (2014)	*Panel*	*Firm Level*	*1994-2008*	*308 supported vs.508 non supported*	*Public financial support (Italian Law 100/90)*	*Internationalization (FDI), Performance (turnover and productivity)*	*SME, Age, Region, Industry, International Experience, etc.*	*Two-step treatment effect analysis (Selection and Evaluation Equations)*	*Significant (+)*	*The moderating effect of variables such as size, age and international experience is investigated and discussed in detail.*

In order to investigate the hypotheses, we use the data related to a local-based R&D program in Province of Trento in Italy. Therefore, in the chapters related to empirical evaluation, we describe and discuss the reference R&D program (policy) evaluated in the following essays. A clear understanding of the R&D support program helps the researcher for a more efficient and effective design of the evaluation framework, data provision, evaluation model(s) modifications and a better choice of instruments to measure the effect of the policy. The related chapter discusses about the place-based R&D program related to the provincial law LP 6/99 and the context and institutional setting of our study.

Chapter 2

R&D subsidies effect evaluation and subsidy mechanism analysis: Research hypotheses

Abstract

Chapter two, following the previous chapter, primarily discusses about the effect of R&D subsidies on TFP change. The discussion addresses the relationship between R&D and total factor productivity (TFP) as a channel which subsidies may influence TFP, beside other channels and interactions explaining the effect of R&D subsidies on TFP change and the components of TFP change. Moreover, the empirical literature of studies dealing with evaluation of R&D subsidies effect on TFP will be reviewed.

This theoretical background beside the topics discussed in the previous chapter, help us to shape the R&D policy evaluation framework, to investigate the direct casual impact of R&D subsidization policy on target outcomes related to TFP change (Chapter 3). The framework also links to the investigation of the effect of firm characteristics in different stages of the mechanism which R&D support program affect R&D expenditure (Chapter 4).

Finally, taking into account the evaluation framework, we hypothesize the research questions based on the theoretical concepts and literature review discussed through the previous and current chapters.

1.Introduction: The effect of R&D subsidies on total factor productivity (TFP)

Previous chapter discussed about the reasons why public authorities design and implement private R&D incentive programs. Beside spillover and network effect,[43] one main justification was to encourage private enterprise to invest additionally on research and development activities to compensate for the usual underinvestment in innovation. Different R&D policies and different types of additionality were defined. Moreover, a literature review of studies which empirically measure the effect of R&D subsidies on additional R&D (input and output R&D activities) has been addressed as well.

[43] Last chapter takes into account spillovers effect in order to model the subsidies effect on R&D input additionality.

On the other hand, increasing economic growth has also been pointed out as one main logic behind R&D policy. Although, public R&D subsidization policy implemented by governments are particularly designed to stimulate private additional R&D activity (input, output and behavioral additionalities), however, one ultimate goal of an R&D policy is the increase of economic growth. *Total factor productivity can be considered as a measure and determinant for economic growth.* The literature investigating investment policies contribution to growth and competitiveness of subsidized firms has gotten large and is still expanding (Bernini et al., 2017).

R&D subsidies may influence TFP growth indirectly through the effect on R&D additionality. If R&D subsidies additionally affect R&D input (R&D expenditure) and R&D input additionality can lead to additional R&D output (such as invention or acquisition of new technology) and subsequently R&D output can influence total factor productivity, then it can be implied that one channel which R&D subsidies may influence TFP change is through additional R&D activity. Sections 1.3 of Chapter 1 explained how R&D subsidies have an impact on R&D additionality, while sub-sections 5.2.1 and 5.2.2 of Chapter 1 reviewed studies investigating the effect of R&D subsidies on input and output additionality. Consequently, this section first focuses on the relationship between R&D activity and economic growth (in terms of TFP productivity). Afterwards, the mechanisms and channels which subsidies may influence TFP will be also discussed. Moreover, we provide a literature review of studies empirically evaluating the net effect of R&D subsidies on productivity mainly total factor productivity (TFP) change. In the following we discuss the former effect by explaining the relationship between R&D and productivity.

1.1. The relationship between R&D activity and Total Factor Productivity (TFP) growth

One indirect channel which R&D subsidies *may* influence TFP is through additional innovative activity. However, the relationship between R&D and productivity growth has been always a debate. Therefore, prior to reviewing the literature related to evaluation of the effect of R&D subsidies on TFP change, we address the relationship between R&D and productivity (and subsequently TFP). Admitting the positive relationship between R&D and productivity growth in the 50s, 60s and 70s studies, Griliches (2007) refers back to the study by Clark and Griliches (1984), in which they found a significant relationship between R&D and total factor productivity growth using data at business unit level in the 70s and 80s. Czarnitzki and O'Byrnes (1999) also find positive elasticity and private and social rates of return to output with respect to R&D investment in many different studies at firm, industry or aggregate levels. A recent meta-data regression analysis by Ugur et al. (2016) investigates the relationship between R&D and productivity for OECD firms and industries. The study finds out a positive average elasticity and rate of return for R&D using 1253 estimates out of 65 primary studies.

Crépon, Duguet and Mairesse (1998) propose their highly cited model of R&D, innovation and productivity known as CDM model, identifying how R&D effort explains innovation and how innovation determines productivity. In the model's structure, market share diversification leads to research and development activity and knowledge capital and patents as innovation output. This innovation output may affect the productivity. There are other exogenous factors such as demand pull, technology push, size and sectoral effects, beside capital intensity and labor quality which affect the model components. CDM model has been modified and extended in different aspects by Griffith et al. (2006), Hall et al. (2013) and Acosta et al. (2015).[44]

Hall et al. (2013) entered R&D and ICT investments into CDM model as input variables for innovation and productivity. Using unbalanced panel data of Italian manufacturing firms for four consecutive waves of surveys, they found out both factors are associated with innovation and productivity, with R&D being more important for innovation and ICT for productivity.

The study by Acosta et al. (2015) modifies and empirically estimates the model, using the data of 541 Spanish firms in food and beverage industry over the years 2008 to 2011. They simply link R&D subsidies to R&D activity as the innovation input and link R&D activity to innovation outputs including product, process and also organizational innovation[45]. The research primarily measures the effect of the public R&D support on R&D decision and R&D intensity and subsequently relates these variables to productivity. The model also includes an equation that determines the relationship between different types of innovation output and labor productivity. This equation estimates the effect of control variables, and it also includes the public R&D support at local, national and EU levels besides many other firms' characteristics.

The contribution of R&D to productivity has typically been measured using the production function including production factors (capital and labor) beside R&D or knowledge stock factor.

[44] Later we also review the paper by Czarnitski et al. (2016) in which R&D subsidies is derived into CDM model.

[45] This is their extension made to the model of Griffith et al. (2006).

This function can be formed at firm, industry or aggregate levels. The interesting determinants to be statistically and empirically estimated are the elasticity of output with respect to R&D or R&D rate of return (Czarnitzki, D. & O'Byrnes, 1999).

A common functional form to measure elasticity of R&D is Cobb-Douglas production function as follows:

$$Y_{it} = Ae^{\mu t} = K_{it}^{\alpha} L_{it}^{\beta} R_{it}^{\gamma} e^{\varepsilon_{it}} \tag{1}$$

where $Y = realized\ output$, $A = total\ factor\ productivity$, $K = capital\ stock$, $L = labour$, $R = R\&D$ and $e = error\ term$ which captures the residual between what is produced in real and what is predicted by the function. This error demonstrates the effect of unobservable factors on production. i denotes firm, industry or country and t stands for the time. Using cross sectional or time series data α, β and γ are the parameters to be estimated to show the elasticities of output regarded to capital, labour and R&D, respectively. Taking log from both sides of equation (1) yields a more straightforward to figure out the coefficients:

$$\log(Y_{it}) = \log(A) + \mu t = \alpha \log(K_{it}) + \beta \log(L_{it}) + \gamma \log(R_{it}) + \varepsilon_{it} \tag{2}$$

Griliches and Mairesse (1984) derive the following equation from equation (2) [by taking derivative from both sides] to measure the R&D rate of return:

$$\frac{\Delta Y_{it}}{P_{i,t-1}} = \mu + \alpha \frac{\Delta K_{it}}{K_{i,t-1}} + \beta \frac{\Delta L_{it}}{L_{i,t-1}} + \gamma \frac{\Delta R_{it}}{R_{i,t-1}} + \Delta \varepsilon_{it} \tag{3}$$

where ΔR_{it} is the net additional R&D investment (expenditure) and γ represents the rate of return for R&D which means an increase in the output for another Euro (or Dollar) being spent on R&D. However, estimating the parameters of production function because of problems related to the omitted variable[46], simultaneity[47] and multicollinearity[48] would be exposed to biases in the results.

Production function approach as defined, provides us with the average measures of total factor productivity (TFP). From a methodological point of view, there is a distinction between

[46] Making unobserved factors to be correlated with R&D.
[47] Simultaneity bias happens when dependent variables are correlated with the error term. For instance if increase in R&D expenditure is dependent on past productivity growth while at the same time productivity depends on R&D spending. IV method is a standard solution to overcome this bias.
[48] Multicollinearity takes place when right hand side variables are linearly related, which would lead to difficulty to disentangle the impact of each regressor (explanatory variable) on explained (dependent) variable. This results in high variance for estimated coefficients.

total (partial) factor productivity which is the ratio between output(s) to input(s), and efficiency, which is the distance from the frontier formed by best performers (Daraio & Simar, 2007). The impact evaluation considering the production function, measures the impact on the average performance while the evaluation dealing with the frontier deals with the best performers (Bonaccorsi & Daraio, 2004). This study follows the latter approach and measures the impact on the firms' relative efficiency change and the technical frontier change carried out by best performers.

Technological progress determines the economic growth in studies which productivity is measured as a residual after controlling for input changes. This approach assumes firms are technically efficient and are operating on the efficiency frontiers. This means the technology is exploited at its full potential. However, firms do not usually operate on their frontiers, hence, TFP calculated in this way does not represent both technological innovation and changes in efficiency. In other words, technological frontier change may not be the only source of TFP change, and technical efficiency change can also play a role in changing TFP (Battese & Coelli, 1995; Jin et al., 2010). In the next chapter, we introduce the approach used to disentangle these sources of change in TFP change.

Understanding R&D-productivity relationship provides insights into the direct mechanism which R&D subsidies may influence total factor productivity through additional R&D activity by the private firm. The firm spending on R&D (innovation input) aims to improve productivity by increasing the proportion of the output(s) produced to the input(s) consumed. This goal can be fulfilled through R&D output (neither sufficiently nor necessarily), including the introduction of a new product or service to the market (product innovation), producing in a more efficient way (process innovation), or even through organizational or marketing innovation.

The best performing firms (firms on technological frontier) are the frontier leaders who may change the production frontier (due to TFP growth) applying R&D subsidies in R&D activities. Firms behind the frontier may increase technical efficiency either by their own additional R&D activity or exploiting the R&D output of technology leaders. At the same time, the firms on technological frontier can also benefit from other frontier firms' R&D output.

If the relationship between R&D and average total factor productivity is positive it does not necessarily show the effect of R&D on the technical frontier but on the average productivity measures. However, if we measure the impact on the best performing firms as decision making units (DMUs), then the impact of R&D input (or output) on the frontier move is measured. The impact of R&D on firm's relative efficiency is estimated by measuring the distance of the firms lying down the frontier determined by the leaders on the frontier.

Empirical research mainly concern the long-run effect of R&D on TFP assuming a Cobb–Douglas type of production function relating output to the traditional factor inputs such as labour and capital, augmented by a TFP term which reflects technological knowledge progress. This technological knowledge is dependent to the level of R&D capital, as measured by cumulated past and present R&D expenditures. This view to the relation between R&D and TFP takes a long run-supply type of interpretation assuming a causality from R&D to productivity. However, in principle, There could be assumed a reverse long-run linkage from productivity to R&D through demand as well (Frantzen, 2003).

Therefore, one important issue to notice, is that the relationship between R&D and TFP can take also an in-directional form. In other words, TFP may also affect the amount of R&D by a reverse causal effect (Baumol & Wolff, 1983). However, Frantzen (2003) investigates The causality between R&D and productivity in manufacturing sector finding out that in at least 16 out of the 22 sectors, the long-run causation of TFP by the R&D variables is significantly stronger than the reverse from TFP to R&D.

The current section addressed the relationship between R&D activity and TFP change. However, R&D subsidies may affect TFP change through other mechanisms and channels. Next sub-section deals with these interactions which links R&D subsidies to TFP change.

1.2 The mechanisms and channels between R&D subsidies and TFP

The empirical literature has not provided explanations about the determinants of the changes in TFP caused by the subsidies. Nevertheless, the theoretical studies have also discussed only about the industrial organization and market structural aspects of the impact of subsidies on TFP growth. TFP change is a productivity measure that identifies the decrease or increase in total output which is not explained only by the increase in capital and labor. The public R&D subsidies can affect *labor productivity* in case the fund is assigned by the firm to reallocate or update the labor input or also because of the capital deepening (the increase in capital per efficiency unit of labor) induced by the subsidies, however, the technical efficiency (measured by TFP) realized by all inputs, may not change (Bernini et al., 2017). Hence, TFP represents the most relevant productivity measure for the efficiency of a subsidized firm (especially an R&D supported firm) to analyze the effects of the subsidies.

TFP growth can capture the dynamics and the mechanisms which link R&D subsidies to performance of the firm. Techniques capable to disentangle TFP growth into decomposed elements such as technical efficiency and technological frontier change, enable us to isolate the effects of the policy into different channels and sources of impact. One which defines the influence of the R&D policy on the firms' relative performance and catching up effort and one which explains the effect of the subsidies on the leading firms' technological improvement.

TFP may be positively influenced by R&D support. Public R&D incentives increase the firms' investment into more know-how labor or in new and higher technological machineries and up-to-dated capital which augments the rate of technological progress of the firm. Moreover, R&D subsidies can provide economies of scope for the firm leading to higher economic performance (Howell, 2017).

On the other hand, the same outcome of R&D subsidies can also negatively affect TFP change. R&D subsidies can stimulate innovative activities and provide new technologies for some firms that do not have skilled technical know-how, which this miss-match can cause reduced total factor productivity (Howell, 2017). In this line, Acemoglu and Zilibotti (2006) and Acemoglu et al. (2007) have argued that the mismatch between skills and new technology can explain TFP difference between less developed & developed countries.[49] This can also be implied for firm level interactions.

Moreover, the firm may deviate from decisions in line with improving allocative and scale efficiency due to the regulation's selection criteria for subsidies assignment. This can lead to a decrease in the technical efficiency change. Another channel for negative effects of subsidies on TFP change can be caused by substitution of labour by capital as a result of the investment subsidies (Harris & Robinson, 2004) and subsidy-induced factor augmentation (Obeng , 2002; Skuras et al., 2006).

[49] Acemoglu (2006: in European Econ. R. 41) discusses that because of this mismatch, in cases, "firms do not invest in new technology and skills, because they expect the future workers to be unskilled."

Furthermore, negative effect can also be explained regarded to the financial flexibility of the firms. as the subsidized loans assignment to financially unconstrained private firms can lead to a productivity slow down due to substantial misallocation of credits and output loss (Zia, 2008). In case of R&D direct subsidies the impact can be even higher. The private firm without financial restrictions receives the direct R&D incentives in form of direct monetary fund to spend on R&D activities which it would not have done without the allocation of the subsidies.

However, the firm without financial barriers most probably could have done the R&D project(s) for which she had received incentives without the public R&D support. However, after receiving the R&D grant, the firm may substitute the credit gained, as the output in terms of the revenue, instead of obtaining the revenue by the same or an increased total factor productivity level derived by innovation activity. Furthermore, the firm can also (mis)allocate the grant in other different activities (either more or less profitable: positive or negative effect) than research and development. The allocation decision influences the productivity change because of different marginal effects R&D activity and other firms' activities can generate on efficiency and TFP changes.

The stream of discussions above dealt with the possible mechanisms and channels which public R&D subsidies may affect TFP change, however, measuring the *overall effect* of different channels of impact on TFP is ambiguous and can be solely investigated by *empirical analysis*.

Referred back to the relationship between R&D activity and economic growth (interpreted in terms of TFP growth)[50], public R&D policy in order to tackle the market failure caused by private underinvestment in R&D[51], encourages private firms to put more effort in innovative activity and to increase R&D expenditure. This additional R&D expenditure can result in additional R&D output which finally may increase TFP growth.

Although the literature widely agrees on the positive influence of R&D on productivity, the dynamics happening between firms in the market with imperfect competition and asymmetric information complicate the analysis. The idea raised by Griffith et al. (2004) for productivity change dynamics for different sectors in different countries, can be extended to firms. Firms lying

[50] This relationship has just been discussed in the previous sub-section.
[51] The traditional market failure and the reasons behind it as a logic for the design of R&D public policy are discussed in detail in the previous chapter.

down the frontier may increase their productivity with a higher rate or return for R&D in comparison to the frontier firms. One main reason for the fast catch up of the frontier can be related to capturing the innovation spillover of the firms on the frontier using their absorptive capacity. This means a lower imitation cost for the followers. R&D investment generates knowledge and knowledge, as an intangible asset can spill out and diffuse across the network to benefit other firms from the positive externality (Arrow, 1962). At the same time, there is a social rate of return for R&D besides the private rate of return.

On the other hand, the firms on the frontier using IPR and patent protection increase their market share and monopolistic strength which may result in higher appropriation and consequently higher revenue. These mechanisms would bring up the question in what direction and to what extent public R&D policy (which encourages additional R&D investment) affects the productivity frontier change and relative productivity measures for firms below the frontier. Later we discuss how the methodology used in this study to disentangle the TFP change into technical efficiency change and technological frontier change components can help us measure these effects.

One main reason to allocate public R&D subsidies to private firms is to increase competitiveness in different industries and sectors by improving relative performance (technical efficiency) of the firm and consequently the technological frontier in the related sectors (OECD, Oslo manual, 2005). Empirical investigation can identify the causal impact of R&D subsidies on TFP growth. However, this black-box systemic approach is in contrary and at the same time complementary to the approach considering the micro effects, mechanisms and the channels, discussed previously. The latter approach explains the link between R&D subsidies to TFP change, clearing up the box. Nevertheless, empirical analysis of the mechanisms connecting the policy in general and R&D policy in specific to *changes in productivity and growth* have always been challenging and ambiguous (Bernini et al., 2017) and is beyond the scope of this study.

2. Literature review of R&D policy effect evaluation on TFP change

Section 5.2.1 and 5.2.2 in Chapter 1, reviewed the literature related to the impact evaluation of R&D subsidies on input, output and behavioral additionality. However, the targeted dependent variable in empirical evaluation studies can differ from additionality. Next chapter aims to measure the impact of R&D subsidies on firms' efficiency change and technological frontier change as the decomposed elements of TFP change. However, R&D expenditure and R&D

intensity are the most common outcome variables investigated in studies related to public R&D subsidies evaluation. In this essay, TFP change has been studied as the target variable different from R&D expenditure or R&D output. There have been studies considering various variables as the target outcome such as technology adoption (Atzeni & Carboni, 2008), doing R&D decision (Czarnitzki et al., 2011), spillovers effect (Takalo et al., 2013), internationalization (FDI) and performance in terms of turnover (Banno` et al., 2014), innovative productivity and follow-on funding (Howell, 2014; Zhao & Ziedonis, 2014), employment, capital investment and turn over (Cerqua & Pellegrini, 2014), survival (Howell, 2014; Zhao & Ziedonis, 2014; Wang et al., 2015) and patenting and new investment(s) (Wang et al., 2015).

A diverse strand of the literature refers to measurement of the effect of R&D policy on other outcome indices different from types of additionality. These indices mainly represent economic growth and proxy the endogenous growth at micro and macro levels. One main target variable representing a relatively comprehensive determinant for economic growth is TFP and TFP change. Total factor productivity represents a suitable outcome variable as it concerns both input and output sides of the production or service system. Consequently, it captures a complete picture of growth both at firm level and aggregate level. Table (1) reviews some of the papers which have taken into account productivity measures as the target outcome variable.

Again, the literature of the effect analysis of different industrial policies on TFP is relatively large, however when it comes to investment policies impact, it radically shrinks. There are few studies which have measured the effect of public capital subsidies on total factor productivity (TFP) change (Harris & Trainor, 2005; Bernini & Pellegrini, 2011; Moffat, 2014; Crisculo et al., 2016, Bernini et al., 2017). Furthermore, the number of papers gets even more scarce when the research focuses on the effect of R&D subsidies on TFP change. There are only few numbers of studies dealing with the effect of R&D policy on TFP dynamics (Colombo et al., 2011; *De Jorge & Suarze, 2011;* Howell, 2017) and among those to the best of our knowledge, only the one in italic resembles the effect measured in this thesis, i.e. the effect on technical efficiency and technological frontier change as a non-parametric decomposition of TFP. The other few studies, use a functional form to investigate the effect of R&D incentives on TFP by simply linking TFP change as the dependent variable to a function of R&D activity and R&D support variables.

Table 1. Studies related to the evaluation of the effect of policies on efficiency and TFP

Study	*Dataset*	*Level of Aggregation*	*Period*	*Observations*	*R&D Policy Variable*	*The Target Variable*	*Control Variables*	*Evaluation Methodology*	*The Effect*	*Notes*
Bernini and Pellegrini (2011)	*Panel*	*Firm Level*	*1995-1998, 2000-2003*	*665 subsidized, 1228 non-subsidized*	*Capital Investment Subsidies (Italian Law 488/1992)*	*Growth, Productivity*	*Size, Sector, Project type*	*Difference-In-Difference Matching (MDID)*	*Significant (+/-)*	*Positive influence in short-run/ Negative effect on long run*
Colombo et al. (2011)	*Panel*	*Firm level*	*1994-2003*	*247 Italian-owner-managed*	*R&D subsidies to high-tech start-ups*	*TFP measured from semi-parametric Olley and Pakes (1996)*	*Age, the ratio of debt to total assets, cash flow to sales ratio, the regional infrastructure development, TFP of the last period, Industry*	*Simple GMM regression*	*Positive(+) impact for subsidies based on competition (selective procedure)/ Negative (-) impact for subsidies allocated by automatic procedure*	*The subsidy variable in one year lagged due to the effect of subsidies on TFP*
De Jorge & Suarze (2011)	*Panel*	*Firm Level*	*1993-2002*	*5349*	*R&D Subsidies*	*Firms' technical efficiency*	*Capital, Employment, Industry, trend*	*Stochastic Frontier Analysis (SFA)*	*Significant (-)*	*Sample of Spanish manufacturing firms*
Bernini et al. (2017)	*5 year panel data*	*Firm level*	*1995–2003*	*255 treated vs. 281 control group*	*Capital subsidies (Italian Law L488)*	*TFP decomposition (Technological change, technical change, Scale and allocative efficiency)*	*Tangible capital, Employees, ROE, Net Liabilities, Cash flow*	*Regression Discontinuity Design (RDD), SFA to decompose TFP*	*Negative (-) impact on TFP in short term/ Positive impact on TFP in long run*	*The positive impact for medium-long term happens through technological change*

In the following, we review few works related to the effect of capital subsidies on TFP change to address the general idea of investment incentives on TFP change. Next, the studies regarding the impact of R&D incentives on TFP change and the paper related to the impact evaluation of R&D subsidies on TFP decomposed elements will be discussed.

Bernini et al. (2017) investigate the effect of capital subsidies on total factor productivity (TFP) growth in short and long terms. They found out the capital subsidies negatively impact the TFP growth in short run, while their effect in medium-long run is significantly positive. This positive effect is mainly influencing through technology changes rather than scale changes. They admit that the policy's aim is to enhance the efficiency and competitiveness as the main factors of endogenous growth and long-term catch up by the laggard firms. However, they emphasize that the relationship between public subsidies and efficiency and productivity is ‘complex and not unique’.

Bernini and Pellegrini (2011) evaluate the impact of capital investment subsidies through the Italian regional policy under the law 488/1992, using difference-in-difference matching estimator (MDID) on employment, fixed assets and TFP growth. Surprisingly, the impact is negative on TFP growth in contrary to other two target variables.

Klette, Møen and Griliches (2000) show Norwegian IT-related manufacturing firms which have used aids from public R&D programs, performed significantly worse than non-supported firms in terms of total factor productivity growth. However, because the government tried to support some high-tech firms which have had a poor performance because of late 80s IT industry restructuring, they do not necessarily conceive a causal relationship between public R&D support and poor performance in terms of total factor productivity. Moreover, they expect this relationship to be in the other way and positive.

In a broader macro perspective, Grossman (2007) compares the impact of R&D subsidies with the public education expenditures on scientists and engineers (S&E) on growth measures such as productivity and welfare. He finds that R&D subsidies can lead to earnings inequality while investing on S&E education will act neutral. The education programs show an unambiguous effect on growth promotion.

Similar to our study in terms of targeted variables and the method used, De Jorge and Suàrez (2011) have studied the effect of subsidies for R&D on technical efficiency as a component of TFP in a sample of Spanish manufacturing firms for the period from 1993 to 2002. They take technical efficiency as the output additionality factor (which is questionable), and use a resource-based view of the firm together with stochastic frontier analysis to measure the effect of the subsidies. They concluded that the firms which receive subsidies for R&D are less efficient. The study analyzes the estimation results by firm size and also by sector (20 sectors). They mention a lack of other works in relating efficiency and subsidies as a reason for no possible comparison between the results.

Zhang et al. (2011) analyze the technological and efficiency changes for 59 research institutes in Chinese Academy of Sciences after the implementation of the Knowledge Innovation

Program (KIP) using the panel data from 1997 to 2005. Moreover, they carried out a regional analysis to find out the institutes in Beijing and Shanghai which performed better than those in the other regions at the same period. They use Malmquist productivity index to decompose productivity change into technological change and efficiency change.

Colombo et al. (2011) measure the impact of R&D subsidies provided to high-tech start-ups on their performance in terms of TFP growth. The logic behind selection of TFP growth as the target variable is that it reflects the influence both on output performance and the efficiency of the use of inputs. The subsidy programs influence both input and output sides. Moreover, they presume that the (opportunity) cost of application for the support especially in selective procedure is high, that if only innovation output measures are considered, the net effect of the policy will be biased. They measure the TFP change by using a GMM method considering the TFP and subsidies provided of the last period as independent variable. The subsidies allocated through selective scheme has a significant positive effect of 31% on TFP change.

Howell (2014) and Zhao and Ziedonis (2014) have estimated the impact of the subsidy program in Michigan and Small Business Innovation Research (SBIR) program. Both studies using documentations for the projects, found out that the causal relationship between being subsidized and the performance remains low. Hud and Hussinger (2015) have measured the effect of R&D subsidy on R&D investment and productivity for SMEs in Germany during the most recent economic crises for the period of 2006-2010. The results estimated using the nearest neighbor propensity score matching, do not show a significant difference between labor productivity for the firms receiving R&D support before and after the crisis. Wang et al. (2015) have also studied the effect of Chinese State Innovation Funding, labeled as Innofund Program, on firm performance. Baum et al. (2017) show sectoral heterogeneity on the relationship between R&D-Innovation-Productivity (RIP) applying a structural model on Community Innovation Survey data related to Swedish manufacturing firms.

Finally, Howell (2017) finds out pubic R&D subsidies reduce firm's economic performance (TFP change) in both lower and higher technological industries despite promoting innovation in higher technology sectors. He investigates the impact on TFP using the structural innovation approach of CDM. The approach links the firm performance to innovation output in an equation which the dependent variable is TFP of time t while the latent innovative activity of the firm is included in explanatory independent variables vector together with other firms' characteristics (determinants) for productivity growth such as size, age and industry characteristics. Subsidy receiving status is also considered as an independent variable.

The research arises the question that why policy makers have insisted on allocating R&D subsidies to firms if the support ultimately reduced their average TFP. A rationale can be that public authorities are willing to tolerate lower average TFP gains hoping that the firms which have already received the funds will finally become successful innovators and generate large TFP gains in the long run and add more to social welfare. Therefore, state supported 'winners' will finally compensate the average efficiency loss of average firms by positive market and technological spillovers out of their successful innovations in a relatively longer term. However, the empirical analysis shows while the 'picked up winners' capture some TFP gains; these gains are smaller than the TFP gains of successful innovators which do not benefit from public support.

In slow growing economies, such as Italy, the allocation of scarce resources to increase productivity is always challenging. This gets more important when the economy experiences a productivity slowdown due to the economic crisis. Therefore, evaluation of the public economic policies can audit and monitor the policy makers' financial allocation decisions. R&D public policy is of no exception (Barbieri et al. ; 2012).

So far, chapter 1 offered a comprehensive overview on theoretical and practical aspects of public R&D subsidies and public R&D policy evaluation, beside the challenges evaluation studies may face in implementation. Moreover, it provided a literature on the impact of innovation policies on targeted outcomes important for the policy maker. Afterwards and in the current chapter, the relationship between R&D and productivity and the channels and mechanisms which may connect R&D subsidies to TFP growth were discussed. The scant literature of the measurement of the net effect of R&D subsidies on TFP change have also been reviewed. As long as the main focus of this study is on the evaluation of the effect of R&D subsidies on target outcomes of TFP change and R&D expenditure, we mainly concentrate on the theoretical background of the direct effect of R&D subsidies on these outcome measures to frame our research hypotheses explained in the following. All other relevant issues discussed in the previous chapter, together with the theoretical concepts and empirical literature related in this chapter are also addressed while constructing the research hypotheses to be empirically investigated.

3. Research hypotheses: conceptual and empirical framework

This section after all discussions related to diverse aspects (discussed in previous and current chapters) of R&D subsidies effect on outcome variables, hypothesize the study's research questions followed by a discussion on how to answer to the question. The framed hypotheses will be investigated through the following chapters of 3 and 4.

-Chapter 3: Research hypotheses

Endogenous growth theories in line with Schumpeter's idea of creative destruction, assume innovative activity as a determinant for economic growth. The effect of R&D and innovation activity on economic growth at the aggregate level has been discussed according to endogenous, semi-endogenous and fully-endogenous growth theories in the first chapter (Schumpeter, 1942; Romer, 1986, 1990; Jones, 1995; Peretto, 1998; Howitt, 2007, Aghion and Howitt, 1998, 2008). Technical efficiency and technological frontier changes as decompositions of total factor productivity (TFP) change can be represented as measures for economic productivity change. Moreover, section 1.1 in this chapter discussed the relationship between R&D activity and TFP.

Empirically, the relationship between public subsidies and in specific public R&D subsidies and efficiency and productivity of subsidized and non-subsidized firms, is heterogenous and complex. The impact evaluation of subsidy policies on the productivity growth answers the question whether, and to what extent, the public R&D policy has influenced the productivity frontier in the economy or specific sector(s).

Measurement of the effect of R&D subsidization program on firms' relative performance, beside additional R&D activity at the firm level, is an essential practice for policy makers due to efficient optimal-oriented allocation of public grants (OECD, Oslo manual, 2005). The measurement helps policy makers and other beneficiary players in the economy to have an ex-post analysis of the policy and its impact to make further decisions on possible policy modifications and changes. However, the literature on evaluation of the effect of R&D subsidies on TFP change is quite scant which were reviewed in section 2 of this chapter. Even if we generalize the policy to all other types of investment subsidies rather than only focusing on R&D subsidies, there are still few works dealing with TFP decomposed measures as the target dependent variables (such as:

Bernini & Pellegrini, 2011; Criscuolo et al., 2016; Bernini et al., 2017). This study contributes to the scarce literature of R&D subsidies impact evaluation on TFP.

The mechanisms and channels which R&D subsidies may influence TFP has been explained in Section 2. One main channel of effect is through R&D additionality. Subsidies can affect R&D additionality which may contribute to TFP growth. There are other mechanisms which can also explain the positive or negative effects of R&D subsidies on TFP. Measuring the overall effect of different channels of impact on TFP is ambiguous and can be solely investigated by empirical analysis. This research empirically measures the net effect of R&D subsides on TFP changes. The factors and channels mediating this effect already reviewed will be applied in the interpretation of the estimated effect of R&D policy on TFP. In other words, we take into account the mechanisms explaining the relationship between R&D subsidies and TFP, but only to support the interpretation of the results obtained from our policy impact evaluation framework.

Moreover, linked to the methodology applied (PSM matching) to measure the policy effect, we can extract some information and discuss about the way, firm's characteristics and agency's selection criteria may influence the impact of R&D subsidies on TFP change. It is worth to state that there is a part of literature which explains the effect of subsidies on TFP change or other target outcomes through the effect on market structure and industrial dynamics of the firms, concerning entry/exit and survival processes (Laincz, 2005). However, this analysis approach is beyond the scope of this study.

All in all, we should restate that this study carries out a direct casual measurement of the impact of R&D subsidies on TFP growth components. However, to discuss and investigate the channels through which the policy affects TFP change in a policy evaluation approach, the research can benefit from the methods which provide the decomposition of the TFP change into technical and technological (in)efficiency. To the best of our knowledge, there are no studies measuring the impact of R&D subsidies on the productivity change decomposed elements using matching method in a quasi-experimental setting.

Hereby, based on the discussions we had about different aspects of the impact of R&D subsidies on TFP change, we can suggest a scheme (Figure 1) which illuminates the effect of public R&D subsidies on TFP growth measures. The scheme can help to build the hypotheses regarding R&D subsidies impact evaluation to be further investigated.

The main goal of this chapter is to scrutinize the impact of R&D subsidies on technological improvement and technical efficiency change applying a decomposition of TFP for a sample of subsidized and non-subsidized firms in a relevant period of time. This provides us the determinants of funded firms' short and long-term growth. Therefore the first hypothesis of this study is formed as the following:

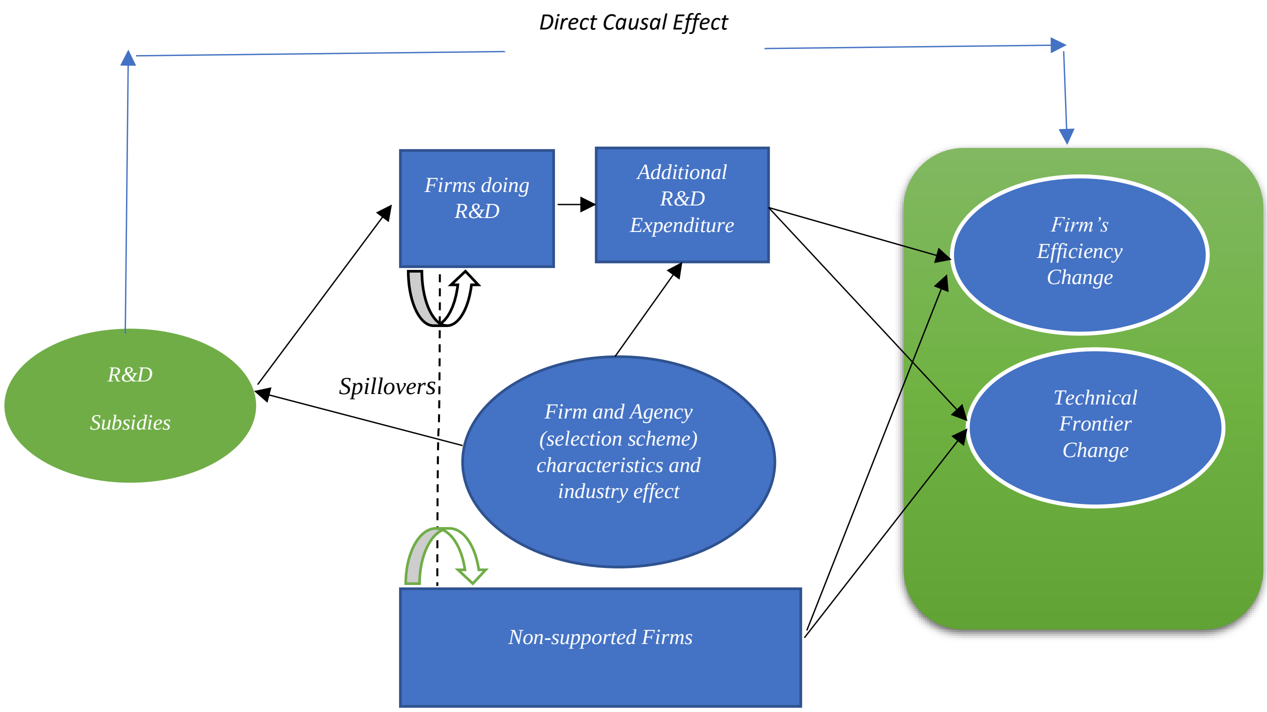

Figure 1. The framework to evaluate the impact of R&D public policy on productivity measures

H.1: Public R&D subsidies affect (positively/negatively) total factor productivity (TFP) growth.

H1.1: Public R&D subsidies affect (positively/ negatively) technical efficiency change (EFFCH).

H1.2: Public R&D subsidies affect (positively/ negatively) technological frontier progress (technological efficiency (TECHCH).

We measure and decompose TFP using Malmquist DEA non-parametric method. Besides DEA there is parametric approach of Stochastic Frontier Analysis (SFA) which has also been widely used in estimating TFP. The advantage of DEA is making no pre-assumption for production function of the firms which is a critical point in case when the impact evaluation has been carried out using a non-parametric method as well. Moreover, DEA only requires input and output data to calculate the efficiency measures. The drawback of DEA method in comparison to SFA is that it cannot assume the presence of stochastic noise term in the production function, which is not expected and assumed in our framework. Nevertheless, Malmquist method is capable to capture technical inefficiency dynamics over time, which enables productivity changes to be decomposed into the change in technical efficiency (i.e. measuring the movement of an economy toward or away from the production frontier) and technological improvement (i.e., measuring shifts in the frontier over time).

This paper, unlike De Jorge and Suàrez (2011) who have used a resource-based view, evaluates the impact of R&D incentives on *different components of TFP* by a quasi-experimental method. In order to evaluate the policy effect, a counterfactual setting for subsidies (treated) and non-subsidized (non-treated) firms can be framed thank to the characteristics and mechanism of the place-based R&D program in Trento Province in Italy. The average treatment effect of the policy on TFP change measures previously calculated is measured for subsidized units (Average treatment effect on treated: ATET) and whole firms (Average treatment effect on the population: ATE) using different matching techniques capable of tackling the problems of endogeneity and selection bias[52] which arise in empirical evaluation studies.[53]

The approach is non-parametric and it does not have to assume any parametric relationship between covariates and the selection (Heckman et al., 1998). Matching takes advantage of no pre-defined structure assumption, however, it has to assume all factors influencing subsidies allocation (control variables) are observable. The unobserved potential outcome of a treated is substituted

[52] Explained in section 5.1.1 in Chapter 1.

[53] Another challenge faced in subsidies empirical evaluation discussed in section 5.1.2 is multiple treatment or co-presence of incentives which must be concerned. However, in our place-base R&D policy context and referred to LP 6/99, the issue of multiple treatment does not bring up much problem as there are restrictions for private firms in the province due to taking advantage and benefiting only from a single source of public support. Although, Since 2015, projects worth up to EUR 100,000.00 can be subsidized together with tax compensation, however, this also does not interfere our analysis as the dataset applied in investigating the research questions does not include the subsidies allocated after 2015.

with the one of a non-treated observation whose characteristics are as close as possible to the treated one. Therefore, the treated group and the control group are formed and we can compare their performance to evaluate the impact of the treatment. However, the more dimensions are included, the more difficult it becomes to find a good match for each treated firm. Propensity Score Matching (PSM) method allows to consider various control variables as matching arguments without suffering the curse of dimensionality. The propensity score is defined as the probability to receive a subsidy and represents a valid methodology to reduce all the dimensions considered to a single index (Rosenbaum and Rubin, 1983; Dehejia and Wahba, 2002). A discussion on the processes PSM scores get generated and different types of PSM techniques will be made in next chapter.

Consequently, a feature of the paper is analysis of the causal effect of R&D subsidies on firm productivity by transforming a local non-random place-based R&D policy into a random experiment created by provincial Law 6/99 (LP 6/99), which has been implemented as a place-based instrument to encourage private R&D in Trento Province. LP 6/99 has been introduced to support applied research projects carried out by private firms active in Trento Province. There are studies in Italian context which focus and discuss about the effect of different selection procedures. Gabriele, Zamarian and Zaninotto (2007), Barbieri, Iori and Lubrano-Lavadera (2012), Bronzini and Iachini (2014), Bronzini and Piselli (2016) have focused on place-based incentives and the different selection schemes to assign the incentives. In our context, subsidies are allocated to R&D projects through screening firms' applications.

There are mainly three procedures to allocate subsidies, namely automatic, evaluative (selective) and negotiating procedures. An automatic scheme gives financial assistant (for expenses up to € 500,000.00), to applicants satisfying the requirements specified in the law and regulations. The selective scheme selects the firms to be subsidized based on the selection criteria (for expenses up to € 1.500,000,00). The applicants compete for receiving a subsidy while their R&D projects are judged financially and technically by committees formed by experts.[54] The negotiating procedure is similar to selective procedure but it supports higher expenses up to € 1,500,000.00. A detailed review of the subsidies program LP 6/99 will be provided in next chapter.

[54] One of the most famous selective programs repeatedly studied (such as the papers by: David et al., 2000; Wallsten, 2000; Howell, 2014; Zhao & Ziedonis, 2014;) in the literature is Small Business Innovation Research program (SBIR) program in U.S.

The selective and negotiating procedures can provide indirect effects for the selected applicants in terms of a certification and confirmation by the government to the firm. Being eligible to get a subsidy signals a higher quality of the firm's project. According to different criteria and settings of subsidies allocation schemes, subsidies allocation schemes can differ in their impact on targeted variables such as TFP change.

Furthermore, in our context, the funds are allocated to applied research projects which presumably represent more development rather than basic research. Public R&D programs have been generally designed to support commercial R&D projects which generate a larger gap between the social and private rates of return (Klette et al., 2000).[55] However, R&D projects are different in their degree of innovativeness, spillover and social welfare effect. Projects tending more towards fundamental research projects may require higher support because of higher uncertainty and lower appropriability in their results.[56] At the same time, the impact and spillover generated by a successful basic (radical) research project will be much higher than other more commercial development projects which are closer to the market.[57]

Although we only deal with applied research projects in law LP 6/99 related to R&D incentive program, however, the expected long term impact of an R&D project can change the subsidy rate. In addition, it is expected that a firm applying for a project with higher technical complications and less skewed to the development side in opposite of fundamental research, probably ask for higher amount of funding. Consequently, the public agency (APIAE) processes this type of application in a scheme different (selective or negotiating) from it would have done in case of lower complexity and technicality (automatic). Therefore, this may result in different

[55] The support for R&D can take two forms of uncertain "far from the market" (e.g. basic research) or "close to market" incentives. Clausen (2009) shows the amount R&D subsidies impact an innovation project is heterogenous dependent to the type of the project. He distinguishes between the effect of the public subsidies to research (R) and development (D) projects. He proclaims that incentives stimulate additional expenditure on research projects while subsidies allocate to development projects close to market substitute.

[56] Private investors would support less the basic research projects which can potentially have high spillover effect. Consequently, the public government must also allocate grants for this type of projects due to hedge a part of uncertainty.

[57] The gap between social and private rate of return for basic research R&D projects is supposed to be higher than development R&D projects. The underinvestment by private entities will be greater for basic research. This stylized fact has been widely agreed in traditional market failure literature. However, the question on how R&D subsidies may differently impact expenditure in research projects in contrary to development projects by private firms, remains unanswered (Clausen, 2009).

subsidies rate which may influence the additional R&D expenditure and total factor productivity change.

After all, the next hypothesis of this study can be declared as:

H.2: R&D subsidies allocation schemes influence on the impact of the R&D subsidies on TFP and its components (technical efficiency and technological change).

In order to investigate the effect of the selection scheme on the impact of the subsidies on TFP growth, impact evaluation using PSM will be carried out for different treatment (subsidies) variable categorized by subsidies allocated by automatic and non-automatic (selective (evaluative) and negotiating scheme). The results will be measured and can be compared with the case when treatment variable includes all types of schemes, to distinguish the effect of the selection method on the impact of policy.

Sector or industry in which the firm operates is an important factor affecting evaluation and selection process. Law LP 6/99 provokes the province to invest more in IT-related industries based on the ICT development horizon emphasized in European Union strategy design and the regional priorities. Industry and sector in which the firm is active have an impact on the technological opportunities and the appropriation condition the firm exposes. Therefore, the R&D investment and activity and consequently the probability the firm applies or receive an R&D subsidy differ between industries (Clausen, 2009).

The different characteristics of the market structure, industrial dynamics (Scherer, 1982; Spence, 1984) and subsequently spillovers (diffusion) in different sectors (Tirole, 1988) can lead to differences in the way a support program affects outcome variables such as TFP change. There is also large literature on the relationship between market size and endogenous growth in industrial organization[58] (Laincz, 2005). this fact can be linked to determining the influence of R&D subsidy program on productivity and technological change through industry characteristics. However, getting more into details of the dynamics of how R&D incentives and subsequently R&D activities

[58] To review the dynamics of R&D activities leading to creative destruction and market dynamics see studies by Jovanovic (1982), Pakes and Ericson (1998). To review the studies related to the micro-market structure characteristics relevant to the incentives for conducting R&D see Klette and Griliches (2000) and Klette and Kortum (2004). To review the studies related to the productivity growth with market dynamic structure see Pakes and McGuire (2001) and Ericson and Pakes (1995).

influence the market structure and growth can be approached by studies related to industrial dynamics focusing on entry/exit and survival effects in the industry which is beyond the scope of this study.

At the same time, the industry effect can be related also to the problem and challenge of heterogenous and mixed findings pointed out in section 5.1.4. Although, a positive relationship between the R&D and firm productivity across all sectors has been found, but Antonelli and Crespi (2013) in their research notify that this positive relationship is much stronger in high-tech firms than in low-tech firms. High-tech firms show "virtuous" Matthew effects while low-tech firms experienced "vicious" Matthew effects, meaning that high-tech firms were awarded subsidies on merit while low-tech firms most often were given subsidies based on reputation and ‘name recognition’, even in case of misallocation of the funds. While the strength of the relationship between R&D spending and productivity in low-tech industries is less than in high-tech industries, studies have been done showing non-trivial carryover effects to other parts of the marketplace by low-tech R&D (Mendonca, 2009).

Almost all evaluation studies have considered the effect of industries on the impact of subsidies on targeted variables, either by taking into account the industry factor as a control variable (Wallsten, 1999; Busom, 1999; Lerner, 1999; Lach, 2002; González, Jaumandreu, & Pazo, 2005; Clausen, 2009; Czarnitzki et al., 2011; Bronzini & Iachini, 2014; Bronzini & Piselli, 2016) or by direct execution of the impact evaluation for particular industries (Klette, Møen & Griliches, 2000; Heshmati & Lööf, 2005; Atzeni & Carboni, 2008; De Jorge and Suàrez, 2011; Acosta et al., 2015; Criscuolo et al., 2016; Marino et al., 2016).

For instance, Barbieri et al. (2012), in addition to the analysis for the whole firms sample, estimate the impacts for sub groups of the firms based on Pavitt classification. Pavitt categorizes firms into four distinct groups including supplier dominated, scale intensive, specialized and science-based. This empirical strategy considers the heterogenous behavior of the firms in response to receiving subsidies for R&D. The authors report that the effect of the R&D policy on target variables strongly changes when they analyze firms in these homogenous sub groups. The authors offer categorization of the firms in sub groups to tackle the heterogenous response problem to be as a common practice in policy evaluation. Moreover, Sissoko (2011) suggests to categorize firms based on the distance to technology frontier. He believes firms far from the frontier are more likely to benefit from R&D support.

A summarization of our data on R&D subsidies, shows funds allocated to firms in five specific industries, are mainly concentrated in manufacturing and ICT sectors. Therefore, the hypothesis of the influence of the industry on the impact of subsidies on TFP change will be as the following:

H.3: The industry and sector the firm performs in, has an effect on the impact of R&D subsidies on TFP change and its components.

In order to investigate the effect of the industry, firms are classified into five main industries[59] in which subsidies allocation takes place. The elaborated classification is carried out using ATECO 2007[60] economic activities coding system (6-digit industry codes). Other industries have not been considered into the analysis as no treatment (subsidies allocation) occurs inside them. The impact evaluation is implemented for each industry (mainly for manufacturing and ICT industries) and for a pool of firms in all industries. The impacts will be compared to check if industry make a difference in the impact's magnitude and direction.

Finally, another main feature of the work is the time interval used for the evaluation. A limitation in many related studies is that they analyse mainly the short-term effect of the subsidies. Hence, using a panel data analysis like the one in our study provides the effects over a long run which can show if the effects of the support through a longer time span is the same as short run effects. The effects measured are likely to be heterogenous, ambiguous and mixed according to the literature. The direction and magnitude of short-run or static effect is almost evaluated without consideration of long-run or dynamic effect stemming from knowledge spillovers and training new scientist and engineers in the long run (David et al., 2000).

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[59] MANUFACTURING- CONSTRUCTION, WHOLESALE AND RETAIL TRADE- REPAIR OF MOTOR VEHICLES AND MOTORCYCLES- INFORMATION AND TERLECOMMUNICATION- PROFESSIONAL- SCIENTIFIC AND TECHNICAL ACTIVITY.

[60] The classification of economic activities (ATECO) is a type of classification adopted by the Italian National Institute of Statistics (ISTAT). It is the Italian translation of the Nomenclature of Economic Activities (NACE) created by Eurostat while being adopted to the Italian economic system. This classification represents the national version of the European coding system called Nace Rev. 2. [See Appendix (3.d)]

Moreover, there can be differences between short term effects (expectedly negative) and long term effects which can be explained by the time to learn, time to stay in a larger market, time to adjust factors proportion and the sluggishness embedded in the impacts of technological improvement (Bernini et al, 2017). This is an important fact particularly for measuring the impact of an R&D policy as the outcome of innovation investment usually takes longer to get realized in comparison with other types of investments. Consequently the next final hypothesis will be explained as the following:

H.4: The impact of public R&D subsidies on TFP change is time invariant. (Or: The effect of the R&D subsidies on TFP growth is different in the short term and long run.)

We scrutinize the impact of the subsidy for each five year of the analysis period thanks to the relatively long time period our elaborated dataset covers. The outcome variable of TFP change together with control variables are lagged to satisfy the setting needed for the impact evaluation.

-*Chapter 4: Research hypotheses*

Up to here, the hypotheses related to the impact evaluation of R&D subsidies on the target outcome have been framed. The empirical investigation of all these hypotheses as also pointed out thorough current section, bears some restrictions both theoretically and empirically. The first main assumption made to empirically test the previous hypotheses is the lack of spillovers in the network because of the empirical approach. Another strong assumption is that all the factors influencing the decision of the firm to participate in the program and the public agency to allocate subsidies are observable. In other words, the selection criteria is totally observable and no unobservable factors may intervene the R&D subsidies assignment.

Consequently, in order to measure the R&D subsidies effect on target variables relaxing these assumptions, this study further estimates a structural model in which spillovers effect may occur and unobservable characteristics can also influence the subsidies allocation and R&D investment behaviour. This can be complementary to the empirical investigation of all previous hypotheses (though on a different target outcome).

Notwithstanding the interactions between different players of the subsidies program and the mechanisms and firm characteristics which may affect different stages of the subsidy program, investigation of the previous framed hypotheses will provide estimations of the causal effect of the

R&D program. However, providing a more detailed model tracing the impact of R&D subsidies on outcome (though different) can shed light on the channels (firm characteristics) influencing the policy features and stages. The firm characteristics are chosen based on literature and the context. For instance, size and age are the main characteristics addressed almost in all related empirical studies (refer to *literature review* of previous and current chapter). Another important factor is exporting status used in many theoretical empirical studies (Zhao, 1997; Yang et al., 2012; Dzhumashev et al., 2016; and refer to the *literature* of the previous and current chapter).

The R&D incentive program in our context consists of different stages of participation and application decision(self-selection stage), evaluation and subsidy rate decision (selection stage) and private firm R&D expenditure (investment decision). Therefore, the next hypotheses are framed as the following:

H.5: R&D subsidies affect additional R&D expenditure.

H.6:[Which] Firm characteristics influence on R&D investment.

H.7:[Which] Firm characteristics influence on R&D subsidies rate.

H.8:[Which] Firm characteristics influence on R&D application decision.

In order to assess the mechanisms related to policy effect in different stages of public (place-based) R&D program, the program is modelled using a benchmark structural model linked to a program including the same stages as our context. However, the empirical estimation of the modified model is adapted based on the main variables related to the contextual setting. Estimation of the structural model including application decision, subsidies rate (spillovers rate) and R&D investment equations, provide us with the marginal effect of firms' characteristics on R&D subsidies and R&D additional expenditure.

4. Remarks

The discussions about the relationship between R&D and economic growth (in macroeconomic terms), R&D and productivity (as a main determinant for economic growth) and the effect of R&D subsidies on R&D activity and total factor productivity (TFP) through previous and current chapters, led us to build a conceptual framework and consequently different research hypotheses.

In order to check empirically the hypotheses, we take advantage of data and information provided by a place-based R&D subsidies program. In the part related to hypotheses on measuring the effect of R&D subsidies on TFP growth, we apply a quasi-experimental setting based on public subsidies allocation and we will use a methodology to compare the outcome between subsidized and non-subsidized private firms. However, measuring the effect of R&D subsidies on the target outcome in this setting ignores the probable spillovers effect and also the influence of unobservable factors on selection and allocation procedures. Therefore, in another part of the research, we concern about spillovers and also unobservables and will apply a structural model to model and estimate the R&D policy.

The rest of the research is organized as follows: Next Chapter 3, before empirical analysis, describes the law LP 6/99 and the place-based R&D subsidization policy regarding the provincial law, besides provision of statistical description of data and variables involved into the essay in favor of the investigation of research hypotheses. The chapter defines extensively the approach applied to carry out TFP decomposition and explains the methodology used to measure the effect of the R&D program on TFP change measures. Moreover, the methodology to measure the effect of R&D subsidies on TFP change will be determined and discussed in detail. Finally the chapter investigates H.1 through H.4 applying these methodologies. The results will be shown, discussed and concluded.

Chapter 4 put empirical and applied effort to scrutinize and answer the research questions H.5 through H.8. The data and variables related to the estimation of the model will be provided. The chapter deals with the effect of firm characteristics on application decision (self-selection), subsidies allocation (selection) and R&D investment equations.

Finally, and after the investigation of the hypotheses, we discuss the implications of the implementation of local place-based R&D program using the topics discussed within the previous chapters and the results obtained.

Chapter 3

Do public R&D subsidies influence Total Factor Productivity (TFP) change? An empirical evaluation of treatment effect

Abstract: Research Framework

The main focus of this chapter is to evaluate the effect of R&D subsidies on TFP growth and the decomposing elements of TFP growth, namely technical (in)efficiency and technological (in)efficiency changes as the determinants of supported firms' growth for a relevant period of time. This evaluation is carried out for the main sectors in which R&D subsidies occur including manufacturing and ICT sectors. The measurement has been implemented for two groups of low-medium tech and high-tech sectors as well. The short-term and long-run effects of R&D subsidies, beside the different treatment effects for two types of selection procedures have also been measured.

This investigation leads to the evaluation of the effectiveness of a public place-based R&D policy. The previous chapter discussed about the channels and interactions explaining the effect of R&D subsidies on TFP change and the components of TFP growth. Previously, a literature on the relationship between R&D and TFP and the studies regarding subsidies impact evaluation on TFP were provided as well. Nevertheless, the policy evaluation framework investigates the casual impact of the policy on TFP change. The theoretical concepts further supports the interpretation of the evaluation estimations results.

We measure and decompose TFP using Malmquist Data Envelopment Analysis (DEA) method. The decomposition can also be carried out using other approaches such as growth accounting and stochastic frontier analysis (SFA). DEA method uses the firm-level data on inputs and outputs (in our setting, 3 inputs and one output for private firms) without any assumption of production function to build the productivity frontier. The relative (in)efficiency of each firm can be calculated based on the distance of the firm to the productivity frontier. Malmquist DEA approach allows for measurement of the inefficiency change over time and has the advantage to disentangle the productivity change into changes in technical efficiency change (i.e. the movement of the firms' production towards or away to the production frontier) or technological change (i.e. shifts in the frontier over time). This provides economic interpretation for the changes in the

growth. The TFP measures are statistically described based on industry and over time in data description section.

The impact of R&D subsidies on technical and technological changes can be measured using a quasi-experimental method. The subsidies allocation mechanism, based on provincial law LP 6/99 related to the assignment of direct subsidies to applied research projects in Trento province in Italy, allows us to form a counterfactual setting in which there are treated and non-treated observations within a time span. We use matching techniques to measure the impact of the public R&D grants on productivity.

Propensity score matching (PSM) is a non-parametric estimator capable of controlling the selection and self-selection biases which occur in evaluation studies. The method measures the average treatment effect on the whole population (ATE) and the average treatment effect on treated (ATET) by comparing the average of the target variables for treated (subsidized) and non-treated units. Whilst a unit cannot be treated and untreated simultaneously, the method matches the treated units with their best matches based on firms' characteristics which influence both the selection and the output variables (known as observables). These observable factors are selected based on the subsidies allocation criteria and other related factors influencing the subsidy decision and the targeted outcome.

The propensity scores are generated due to the balancing of pre-treatment variables (age and size in our setting), in a way which leads to the uncorrelatedness of the subsidies allocation (treatment) to the firms' characteristics (observables). The propensity score distributions are illustrated in the related section. Given the propensity scores, output (target) variables must be uncorrelated with the subsidies allocation as well (unconfoundedness). After these hypotheses are satisfied the average treatment effect is the comparison between the outputs (TFP and firms' productivity components changes) of the treated and control units. Due to check the robustness of the estimations, we measure the effect of R&D subsidies *on all TFP measures* for *the whole population and treated units* (in *different sectors*, *different selection procedures* and for *short-term and long-run* time span) using *PSM nearest neighbor estimator* (with two different estimation process) and *PSM kernel estimator*.

Other features of the study as discussed in the previous chapter, is to capture the effect of the public subsidies allocation schemes (procedures), industry structure or time (short term and long run effects) on the policy implementation, to shed light on different aspects of R&D policy evaluation. The estimations are possible due the construction of a detailed dataset which is the elaboration and combination of datasets related to firms' financial statement and balance sheet dataset extracted from AIDA dataset and the dataset provided by ISPAT and APIAE on the public R&D subsidies allocated to the firms in Trento. The whole procedure leading to construction of the final dataset is discussed as well.

The main findings about the direction of the policy effects on TFP measures reconfirms the part of the literature declaring the mixed and heterogenous results for the effect of R&D subsidies on outcome targeted variables. However, it can be implied that the R&D place-based program affect negatively on technological frontier progress (growth) of subsidized firms and positively on efficiency change of subsidized firms (in ICT sector) in the long run. The R&D subsidies have no effect on growth (in terms of TFP change) in steady state, while they show some positive impact in transient state. This observation is more in line with semi-endogenous growth theory discussed in chapter one. On the other hand, for the whole firms regardless of being treated or not, the program affect positively on efficiency change in the long run (manufacturing sector). R&D subsidies affect negatively on technological progress in long run for all sectors.

All in all, R&D subsidies affect negatively on TFP change in manufacturing and low-medium tech industry. This negative effect mainly holds for the grants allocated automatically to R&D projects rather than allocation based on pre-evaluation or negotiation for selection.

Investigation of the effects of a local place-based public R&D subsidies program for private firms is crucial to assess the effectiveness of innovation public policy designed to stimulate the productivity and thus the competitiveness in a specific context. Literature on investigation of investment policy contributed to growth and competitiveness of subsidized firms has gotten large attention and is still growing. However, the empirical evidence has provided mixed and heterogenous results sometimes even opposite to each other. Empirical evaluation besides the theoretical concepts related to the impact of public R&D subsidies on TFP change, measures and explains the effect of R&D policy and the interactions of the features within a policy model.

In the following before investigating the hypotheses H.1 through H.4 explained in section 5 of Chapter 2, the place-based R&D subsidization program will be discussed to provide us with a more detailed picture of the R&D policy to recognize the important factors influencing the effect of R&D subsidies on total factor productivity. In addition, data and variables applied to measure the policy impact will be also described. Afterwards, the methodologies to measure this effect will be explained and applied. Finally, we analyze and conclude the results.

1. R&D subsidy program related to law LP 6/99 and institutional context

In order to investigate the hypotheses, we use the data related to a local-based R&D program in Province of Trento in Italy. Therefore, in the chapters related to empirical evaluation, we describe and discuss the reference R&D program (policy) evaluated in the following essays. A clear understanding of the R&D support program helps the researcher for a more efficient and effective design of the evaluation framework, data provision, evaluation model(s) modifications and a better choice of instruments to measure the effect of the policy.

This section is about the research context and the provincial law LP 6/99 regarding subsidy allocation program. Data related to the program used for policy impact analysis and model estimation will be described and summarized in each related chapter. Previous sections broadly explained the theoretical and empirical reasons and importance for R&D policy at different levels of aggregation. Different types of R&D policies and their features were discussed, while the focus tended to public R&D subsidies as the main policy being evaluated in this study. Studies dealing with impact analysis of public R&D subsidies were reviewed to highlight different aspects of policy evaluation which research have taken into account.

The current and next chapters will empirically estimate models in which the effect of public R&D subsidies on target variables of productivity growth and R&D expenditure, are measured at firm level. Datasets related to the regional public R&D policy and firms in the region are used to carry out the estimation of the R&D policy model and evaluation of the place-based R&D policy. The data on R&D grants allocated by autonomous province of Trento in northern east of Italy to active firms in the region with R&D projects (in the form of applied research projects) is provided by the responsible provincial agency (the provincial agency for the promotion of economic activities (APIAE[61]), while the data on firms' characteristics in Trento province is provided by other different datasets.

This section defines and discusses about the context and institutional context of the study, focusing on the provincial law and regulations which make the public authority to allocate R&D subsidies to the firms in the region. It also describes the mechanism and the process in which APIAE assigns R&D subsidies to firms. The mechanism includes application decision and different evaluation procedures before providing firms the R&D funds.

In order to answer the research questions, we apply datasets related to a local placed-base innovation policy, i.e. the provincial R&D subsidies program. We call the policy, placed-base and not a regional policy because regional policy is handled by the state mainly to fill the gap for the disadvantaged regions which are less developed (See e.g. Accetturo & De Blasio, 2012), while the local instrument particularly targets the private firms inside a specific region (Barbieri, Iorio & Lubrano-Lavadera, 2012). A placed-base incentive program is implemented by the local government. Place-based policies have received scant attention despite their relative large share of public transfer to private sector. In Italy, Bondonio and Greenbaum (2007), Gabriele, Zamarian and Zaninotto (2007), Barbieri, Iorio & Lubrano-Lavadera (2012), Bronzini and Iachini (2014) and Bronzini and Piselli (2016) have focused on place-based incentives.

In the following we describe and discuss about the local provincial law LP 6/99 which regulates the public R&D subsidies application and allocation to the private firms in Trento Province in Italy. However, before that it is worth to briefly review the regulations regarding a more aggregate level. The next section explains some details about R&D subsidies in Italy.

1.1 R&D subsidies in Italy

The Italian economy, as one of the largest economies in the world, is characterized by low private level of investment in R&D. The private expenditure in R&D is only %40, while the share is around %70 for other European countries such as Finland, Germany, Ireland or Spain. R&D

[61] Provincial Agency for the promotion of economic activities [Agenzia Provinciale per l'Incentivazione delle Attività Economiche (APIAE)]: A detailed script of laws and regulations of provincial law in March 28, 2009 which led to creation of APIAE is provided in the official documentations.
http://www.apiae.provincia.tn.it/index.html

incentives represents %13 of public governmental incentives. This amount is around %15 for Germany, %16 for Spain and %23 for France (Barbieri et al, 2012).

Law 46/82 has been the most highlighted public R&D policy which has lasted the longest among other government R&D policies. The law consists of two main parts: the first part (art. 1-13) which introduces the funds to facilitate applied research (FAR) and the second part (art. 14-21) which supports experimentation, development and pre-industrialization of R&D projects carried out by private firms (FIT). The Italian firms in cases can take advantage of receiving local grants in addition to the funds allocated by the law. This could have happened particularly in the case of the firms in more disadvantaged regions due to introduction of legislations to fill the technological gap between the regions in recent last decades.

The Legislative Decree n. 297/1999, which being reinforced in 2001 has unified many public programs related to support for research and development. The law aggregates programs namely, Law 46/82, Law 488/1992 (the part linked to research), Law 346/1988, Law 196/1997 (art. 14), Law 499/1997 (art. 5) under the title of Fund to Facilitate Research (FAR). Moreover, there have been other laws offering subsidies to innovative activities such as Law 140/1997 (for fiscal grants to R&D expenditures), Law 357/1994 that reduces taxes for reinvestment in instrumental goods and Law 598/1994 that offers low interest rate loans to SMEs spending on innovation (Barbieri et al., 2012).

Merito et al. (2007) have applied a matching method to measure the effects of Fund for Applied Research (FAR) program regulated by art 1-13 within law 46/82 on target variables such as sales, employment, labour productivity and patents. Poti` and Cerulli (2010) have also investigated the effects of this program on additional investment and patents using a combination of a system of equations and matching method. The second part of the law 46/82 (art 14-19) dealing with Funds for Technological Innovation (FIT) has also been analyzed by De Blasio et al. (2009). They found no significant effect on firms' investment using a regression discontinuity approach. At the same time, the Ministry of Economic Development (2008) claims that the FIT has stimulated the R&D investment following a qualitative approach and direct interviews.

1.2 Trento Province, Law LP/699 and APIAE

A systematic approach to entrepreneurship and innovation in Province of Trento, Italy, dates back to 1999, when the provincial law LP 6/99[62] was introduced to support applied research projects at the firm level. According to Law 6/99, incentives can be given to firms operating in Province of Trento for research and development expenditures. Articles 5 and 19 of the law 6/99 address policies regarding R&D investment incentives in the name of support for the promotion of research and development and the dissemination or diffusion of scientific research, respectively[63]. Law 6/99 supports R&D cooperation which develops the relation between science and industry by facilitating knowledge transfer. Additionally, law 6/99 encourages the recruitment of skilled personnel and the mobility of researchers in and between enterprises.

Law 6/99 has been modified under the provincial law of 2 August 2005[64]. Law LP 14/2005[65] reorganized the Trento research system by introducing a new selection and evaluation procedure to support scientific and industrial research financed by the firms in line with law 6/99. Article 57 of the provincial law, regulated in March 2009, establishes the provincial agency for the promotion of economic activities (APIAE) as an administrative body.[66] The APIAE works to strengthen the effective lending and disbursement of aid, contributions, and financial incentives in favor of entrepreneurs and other stakeholders in all economic sectors except agriculture. The APIAE is the public agency responsible for project screening, evaluation, grant allocation and monitoring in the province of Trento. The agency is expected to increase business *efficiency and effectiveness* through "granting aids and credit facilities to firms, in all sectors apart from agriculture."

[62] LEGGE PROVINCIALE 13 DICEMBRE 1999, N. 6, ART. 5, ART. 19 E ART. 19: BISCRITERI E MODALITÀ PER L'APPLICAZIONE DELLA LEGGE
[63] The detailed description of actual law and the acts can be provided.
[64] Our impact evaluation framework applies data after this period, hence there is no mismatch due to the change in selection schemes which can interfere or deteriorate the analysis results.
[65] The year 2010 is another important milestone in the development of the regional innovation system by setting the new multi-annual research program (or PPR 2010-2013).
[66] We assume that introduction of APIAE as the reinforcing body of the province to allocate R&D grants does not generate noise or distortion in the data, as the selection criteria to assign the subsidies remain the same. However, investigation of the effect of establishment of APIAE on the mechanisms subsidies impact targeted outcomes can be an interesting future empirical research issue.

APIAE aims to increase competitiveness in the region by providing grants or guidance to entities *conducting applied research projects* or *diffusing knowledge*. Since July 2011, it is also responsible for verification and control of the research projects in addition to managing relations with consortia, providing financial guarantees and assigning scientific and financial experts to evaluate/select eligible projects. Applications to access the contributions include: support for industrial research projects, support for experimental development, the temporary assignment of researchers and technical research institutes operating in the province, hiring researchers and research technicians from research organizations and academic institutions. The agency deals with the management of grants and financial incentives provided by the provincial laws, as well as the activities related to monitoring and control. The management of relations with the guarantee consortia present in the province of Trento and other credit institutions is also among the responsibilities APIAE is in charge.

The Provincial Agency for Promotion of Economic Activity (APIAE) is divided into two departments; first, the Department of Investment Promotion which carries out the allocation and disbursement of financial aids to support fixed investments of business and other stakeholders operating in all economic sectors (except agriculture). The department also monitors external bodies in charge to manage the operations of supporting fixed investments, runs inspections and checks on the facilitated initiatives, and is responsible of managing the information concerning the activities.

Second, the Finance, Research and Development Department which ensures the allocation and disbursement of financial aids to support business services, research and equity loans in relation to all economic sectors (except agriculture). It also monitors external bodies in charge to manage the operations in supporting business services, research and equity loans and provides analysis, studies and research related to incentive policies, while doing inspections on the facilitated initiatives. The link between research and industry and creation of a motivating environment for innovation is managed by the province through law 6/99. However, the outcomes and impacts of the initiatives of the law have not been evaluated in a systematic way. An evaluation of effectiveness of the law has been launched by APIAE for the period of 2001-2010 and a first report was completed in 2011.

This study deals with subsidies for industrial research projects and experimental development projects. The expenditures eligible for the support consist of a) expenses for employees including the expenses of the owner and partners, b) spending for research contracts, skilled technicians and patents, d) additional expenses for market search, e) other operating costs, and f) costs of tools and equipment. In this study the focus is on support for industrial research projects from now called alternatively as R&D projects or just projects.[67] One can categorize all these expenses under the total R&D expenditure category.

As long as the subsidies are allocated for one of the above five expenditures categorized in the list, studying the impact of the program on TFP change can be focused and linked to these sources of input additionalities. However, the framework of this research investigates a casual effect regardless of the micro-channels which may lead to TFP change. Nevertheless, we will use these eligibility conditions to interpret the results of the impact estimation. It is worth to say that in our study the focus is on the support assigned for industrial research projects from now called alternatively as R&D projects or just projects.

Here we review some other empirical concerns linked to LP 6/99 which could have arisen challenges for the evaluation. Since 2015, projects worth up to EUR 100,000.00 can be subsidized together with tax compensation. However, this does not interfere and distort our analysis as the dataset applied in investigating the research questions does not include the subsidies allocated after 2015. In addition, the assumption that firms applying for LP 6/99 R&D subsidies must renounce the receipt of any other public support relax the problem of multiple treatment or hidden treatment. Furthermore, the probable existence of spillover violates the stable unit treatment value assumption (SUTVA: discussed in previous chapter), which can cast doubt on the impact estimation results. However, in this chapter we assume of no spillover effect of R&D subsidies on TFP change for non-treated units. Finally, it is worth to notice that the policy's local dimension allows for the removal of unobserved heterogeneity among private firms in comparison with the R&D programs nationwide in which the recipients and non-recipients are less similar.

[67] Theoretically, public R&D subsidization policy implemented by governments are particularly designed to stimulate private additional R&D activity (input, output and behavioral additionalities), however, one ultimate goal of an R&D policy is the increase of economic growth.

1.3 Grants for Applied Research Projects: Application and allocation of grants

Applications for subsidies, on the basis of the elements that characterize them, are examined in accordance with the procedures of automatic type (for expenses up to € 500,000.00), evaluative (for expenses up to EUR 1.500,000,00) or negotiating (for higher expenses to EUR 1,500,000.00). All eligible firms can apply for subsidies for their projects and then the submitted projects are technically and financially evaluated by APIAE. Since 2015, projects worth up to EUR 100,000.00 can be subsidized together with tax compensation.

Although there are common requirements in all three project evaluation methods, but the evaluative method includes some more criteria and stages of evaluation and requirements for application in respect to automatic procedure. The same holds for negotiating procedure in comparison with evaluative and consequently automatic procedures. The detailed description of the procedures and the requirements for application through one of these evaluation methods can be accessed from related documents for law 6/99 available online in province's or APIAE's websites. Evaluation turns out which projects get accepted or rejected to receive subsidies. Those accepted are assigned a contribution of the total R&D investment (subsidy rate) by APIAE. Subsequently, the contribution is awarded and injected to the projects in different stages while the firms are running the R&D projects. *All the firms operating in the province of Trento are eligible to apply* for the subsidies by submission of a project to the province. The grants can be applied at any time and there is no deadline to submit a project. However, the projects are evaluated by time order they have been submitted.

The law LP6/99 objectives include stimulating *additional private R&D* and stabilizing the employment rate which leads to a *higher productivity and competitiveness* of the firms active in the region. The agency is responsible for assignment of subsidies to different types of R&D in two categories of industrial research and experimental development. Industrial research is defined as a planned activity aiming at acquiring new knowledge that is used to introduce new products, new processes and services and those activities which concern improvement of the quality of existing products, processes and services. Experimental development is defined as the acquisition, recombination and utilization of existing scientific, technological and commercial knowledge in order to produce projects, products, processes new to the firm or enhanced projects. The creation, construction and development of prototypes are in the latter category (Corsino et al., 2012).

In automatic procedure of project evaluation the subsidy depends to the PRP[68] or NO PRP status of the project. The automatic procedure is assumed to be just for projects related to SMEs. A firm will get a 20 percent of contribution from the public agency if R&D project is determined as PRP, otherwise the contribution for the R&D project will be 15 percent in case the application get accepted by the APIAE. In evaluative procedure, the projects are examined at a first stage of evaluation procedure by a technical committee. If the application is admitted, then at the second stage the project's economic viability and financial sustainability get estimated. If a project gets a positive evaluation at both stages, it can be subsidized by the local government according to the scheme reported in Table 1. Firms are divided into three size classes of small, medium and large defined according to the OECD classification. The contribution is *supposed to be* higher as the firm is smaller. Small and medium sized firms represent the most important share of the industry in this region, as well as the whole Italy. Projects involving industrial research are awarded a higher share of financial support than programs focusing on pre-commercial development.

Table 1. Scheme for rates of subsidies for different types of R&D projects assigned by APIAE for the firms operating within the province of Trento.

R&D Project Type	Small firms		Medium firms		Large firms	
	PRP	No-PRP	PRP	No-PRP	PRP	No-PRP
Industrial Research	70	60	60	55	50	45
%Maximum	80	70	75	65	65	65
Experimental Development	45	40	35	30	25	20
%Maximum	60	50	50	40	40	30

All numbers are in percentage (%)

Source: *APIAE (Provincial Agency for the promotion of economic activities)*

The contribution to R&D project may be raised more than the amount predefined for some specific conditions[69]. The percentage of the contribution is 15 percent more in the case of collaboration with other companies, 15 percent by collaborating with search bodies inside the

[68] PRP is the R&D activity with long term effect in the Provincial Research Program defined by the Law 6/99. Projects in the districts of ICT, sustainable buildings , renewable energy and land management, and spin offs or start-ups doing research are amongst cases to be considered as PRP.
[69] This extra contribution is called as MAGGIORAZIONI.

province, 5 percent to projects collaborating with research bodies out of the province, or a 15 percent to only industrial research projects which their results are disclosed or available in free accessed databases or disclosed by a free software or open source[70].

The range of gross spending for projects is between 25,000 to 3 million Euros. Expenses usually fall in the following categories: (1) employment costs: additional high skilled workforce employed to work on the project, (2) patenting costs and contractual costs of licenses acquisition, (3) general additional costs related to the project (overhead up to 60% of costs declared at point 1), (4) part of costs related to the use of the tools and machines employed within the project. It is worth to restate that these categories which the subsidies are allocated can be applied in interpretation of the estimations regarding the causal effect of subsidies on targeted variables.

Once a firm is awarded a grant, it must obey to some constraints in order to actually get financed: (a) the results of the research have to be used/exploited in the province of Trento, (b) in case the subsidy is bigger than 500,000 Euro or if the firm ask for an additional percentage to the amount of investment financed, it must guarantee, for at least two years since the grant is awarded, the *level of employment declared in the projects*. Projects can entail expenses referred to a period going from the date of concession to the following three years.

A firm doing R&D has to apply in order to receive subsidy *for a planned project*. We expect a firm to apply if the R&D project has a net profit higher than zero considering *the application cost and fixed cost for the R&D project into account.* As long as the subsidy rate for R&D investment is not revealed before the authority's grading, the firm decides to apply supposing an expected subsidy rate for the project. Expected subsidy rate is the amount assumed to be allocated for the project based on the common knowledge and information for the agency's grading process. As described, the evaluation process is carried out in two stages; technical and economic or financial assessments.

The section has explained the national (Italian) public R&D subsidization policies and focuses on the R&D grant policy in Province of Trento as a placed-base R&D subsidy program linked with Law LP 6/99. The application for funds and the selection and allocation mechanisms

[70] A logic model of the table which describes the firm expected rate of subsidy before applying for the projects will be provided in the appendix of next chapter. However, the equation related to table is not used in our econometric estimations within the next chapters.

are discussed as well. All these topics reviewed in this section are the foundation for carrying out the empirical evaluation of R&D subsidies and measuring the effect of the R&D program on TFP change and R&D input additionality in the following chapters.

At this point and after a review of the place-based R&D subsidies program, the hypotheses H.1 through H.4 explained and framed in the previous chapter will be investigated. In a theoretical perspective (as the main foundation for the research questions), we have extensively discussed the relationship between R&D subsidies and total factor productivity (TFP). In addition and on a more practical perspective, the law LP6/99 objectives include stimulating *additional private R&D* leading to a *higher productivity and competitiveness* of the firms active in the region. Therefore, measuring the effect of R&D subsidies on productivity change and the related peripheral research questions (H.1_H.4) are the main focus of the essay in this chapter. We repeat the hypotheses for easier reference in the following:

H.1: Public R&D subsidies affect (positively/negatively) total factor productivity (TFP) growth.

H1.1: Public R&D subsidies affect (positively/ negatively) technical efficiency (EFFCH) change.

H1.2: Public R&D subsidies affect (positively/ negatively) technological frontier progress (technological efficiency (TECHCH).

H.2: R&D subsidies allocation schemes influence on the impact of the R&D subsidies on TFP and its components (technical efficiency and technological change).

H.3: The industry and sector the firm performs in, has an effect on the impact of R&D subsidies on TFP change and its components.

H.4: The impact of public R&D subsidies on TFP change is time invariant. (Or: The effect of the R&D subsidies on TFP growth is different in the short term and long run.

In order to investigate H.1, total factor productivity (TFP) and the decomposition of TFP change must be defined. Hence, in the following we explain the approaches and the methodology used to measure the TFP change and the components of TFP change.

2. Methodology

2.1 Models and methodologies to measure changes in TFP and TFP components

The targeted outcome variable this study focus on is total factor productivity change. Firm technical (in)efficiency and technical frontier (technological) efficiency changes are the measures determining total factor productivity change. Technological progress determines the growth in production, in studies which productivity is measured as a residual after controlling for input changes. This approach assumes firms are technically efficient and are operating on the efficiency frontiers. This means the technology is exploited at its full potential. However, firms do not usually operate on their frontiers, hence, TFP calculated in this way represents both technological innovation and changes in efficiency. Consequently, technological frontier change may not be the only source of TFP change, and technical efficiency can also play a role in changing TFP (Battese & Coelli, 1995; Jin et al., 2010).

Malmquist Data Envelopment Analysis (Malmquist DEA) is widely used to study production efficiency dynamics. The technique provides us with estimation of both technical efficiency and technological change over time. Before, explaining the method which is applied in this study to isolate the effects of policy on TFP components, we follow a brief description of how the model is constructed.

Farrell (1957) introduced technical efficiency as the ability of the firm to obtain the maximum set of output(s) from a given set of input(s) and price efficiency (allocative efficiency) as the ability to allocate optimal proportions of input(s) to produce a given amount of output according to their respective prices. The overall (economic) efficiency is measured by combination (multiplication) of technical efficiency and allocative efficiency as $EE_i = TE_i \times AE_i$, where TE_i= technical efficiency, AE_i= allocative efficiency and EE_i= overall economic efficiency.

Farrell using agricultural data for 48 states in United States and following Debreu (1951) and Koopmans (1951), determines the above measures in input and output oriented forms using simple examples of two inputs-one output and one input-two outputs production system under the assumption of constant return to scale. The former takes the input reducing approach and answers the question that “how much can input quantities be proportionally reduced without any change in the output produced”, while the latter deals with output maximization orientation and answers the question “how much can output quantities be expanded without any change in the inputs consumed". The illustration and discussion about graphical representations of isoquants can be found as a primary topic in the books related to efficiency and productivity analysis.

A strong assumption in Farrell's paper is that fully efficient firms' production function (a unit isoquant in this case) as discussed above is known. However, the frontier of all efficient firms is unknown in practice. Thus, he suggests for future studies to form the frontier by using either a piece-wise-linear convex isoquant using sample data or shaping a stochastic parametric function such that any points lies to the left (right) or below (up) the efficient frontier in input(output) orientation.

Two principal methods used to estimate the frontier and consequently relative inefficiency of firms lying down the frontier are non-parametric mathematical programming Data Envelopment Analysis (DEA) and econometric parametric Stochastic Frontier Analysis (SFA). The former is introduced by Charnes, Cooper and Rhodes (1978) while the latter is introduced by Aigner, Lovell and Schmidt (1977) and Meeusen and Van denk Broeck (1977).

The frontier in DEA is formed using information about inputs and outputs, while SFA estimates the frontier assuming a specific production function *per se*. SFA assigns a non-negative random variable (one-sided normal distribution) to technical efficiency term in the production function and a stochastic error term which is independent identically distributed *(i.i.d)* normal distribution with mean zero, capturing the measurement error and environmental shocks influencing the output production. Although SFA solves the problems of deterministic efficiency measurement models like Maximum-Likelihood models which ignore the 'noise' in measurement, however, one main drawback of SFA method is *a priori* assumptions for stochastic components of the stochastic production function.

Assuming a production function like for instance Cobb-Douglas production function to measure realized output, yields the average amount of output. However, as discussed the hypotheses aim to estimate the frontier either to measure technological change carried out by the best performers or to capture the relative (in)efficiency of the firms with respect to that frontier. Therefore, we need a methodology to let us relax the assumption for the production function form.

DEA-based Malmquist Productivity Index is a widely used approach which solely uses input(s) and output(s) distance functions to measure total factor productivity (TFP) change and its components including relative efficiency change and the technological frontier shift (Färe et al., 1989 and 1998). Caves, Christensen and Diewert (CCD:1982) introduced the geometric measure of MPI referring to the definition introduced by Sten Malmquist (1953) for input quantity index. In the following and before explaining Malmquist Productivity Index, DEA approach and distance function definition are defined as the basis for MPI measurement.

2.1.1 Data Envelopment Analysis

The DEA approach is based on a non-parametric linear programming model introduced by Charnes *et al.* (1978) known as CCR (Charnes, Cooper and Rhodes) model following the study of Färrel (1957). The model measures the production frontier for homogenous entities[71] only by using the data on inputs and outputs of decision making units (DMUs) without concerning the production function. The relative (in)efficiency of each DMU is measured calculating the distance of the DMU with the enveloped frontier shaped by best practice DMUs. This frontier can be formed under either Constant Returns to Scale (CRS) or Variable Return to Scale (VRS) assumptions. The DEA model under VRS technology is known as BCC model being introduced by Banker, Charnes and Cooper (1984). The measure for efficiency is as the following:

$$E_j = \frac{Weighted\ sum\ of\ Output(s)}{Weighted\ sum\ of\ Input(s)} = \frac{u_1 y_{1j} + u_2 y_{2j} + \cdots + u_t y_{tj}}{v_1 x_{1j} + v_2 x_{2j} + \cdots + v_m x_{mj}} \tag{1}$$

where y_{rj} denotes the amount of output r for firm j, u_r is the weight (price) for output r, x_{ij} is the amount of input i for the firm j and v_i is the weight (price) of input i. The notations are chosen as in the seminal work by Charnes et al. (1978). The ratio can be measured straightforward for entities or in general decision making units (DMUs) when there are one input and one output involved in the production (service). Even if there are cases for two input/one output or one input/two outputs, one can measure the proportions of output/input and map the efficiency frontier due to calculate relative efficiency. In case there are multiple inputs/ multiple outputs (MIMO) estimating the ratio would face challenges because the weights for each input/output must be realized. DEA methodology is capable of calculating the relative efficiency measures when there is MIMO

[71] Decision making units which have a similar process of transferring inputs to outputs.

condition. DEA models have been extensively developed to address many challenges and gaps related to specifications and applications of the model.

The model has different representations based on primary or dual forms and input or output orientations taken towards maximization of the efficiency ratio. While the algorithm empirically used to estimate the distance to the frontier applies a dual form of DEA and constant return to scale (CRS) output orientation, we explain CRS Output-Oriented DEA dual model. A discussion of other basic types of DEA models and how the mentioned model is formed can be found in the appendix (3.a).[72]

$$Max\ \theta$$

$$s.t. \sum_i \lambda_i x_{ji} \leq x_{jn}\ \forall j$$

$$s.t. \sum_i \lambda_i x_{ji}\ \geq \theta y_{kn} \forall k$$

$$\lambda_i \geq 0\ \ \forall i$$

DEA CRS Output-Oriented dual model (2)

DEA model using input and output data of DMUs shapes the efficiency frontier and measures the distance of each DMU from the frontier due to measurement the technical (in)efficiency. The frontier and the distance to frontier can be captured through time intervals to estimate efficiency change and technical frontier change. The method used to make this possible is Malmquist Productivity Index approach based on calculation of distance measures. The following section discusses distance function and MPI.

2.1.2 Distance function and Malmquist Productivity Index (MPI)[73]

Index number theory is the most widely used approach to measure changes in levels of economic variables. Quantity and price index numbers are widely used in measuring output and

72 The basic DEA model primarily proposed by CCR (1978) and the linear form and after dual form, as well as the BCC extension (1984) to the model are explained.

[73] The models and definitions are a combination and adaptation of formulations in (Caves et al., 1982; Bjurek, 1996; Lovell, 2003; Camanho & Dyson, 2006)

input changes to measure productivity change over time. Total factor productivity (TFP) is one of the index numbers used as a base to measure the related productivity measures in empirical productivity analysis studies. In case of one input and one output, measuring this index number will be straightforward, however when there are multiple inputs and outputs, the need to aggregate the TFP index number emerges.

The index number introduced by Tornqvist (1936) is a seminal effort to measure total factor productivity index. Malmquist productivity index was first theoretically introduced by Caves, Christensen and Diewert (1982) and empirically applied by Färe et al. (1994). The index is actually the proportion of Tornqvist output index to input index used to measure the productivity change over time regardless of price information in contrast with Fisher Index.

The Malmquist Index can take input or output oriented definitions. Input or output orientated technical efficiency measures explained in the previous section are equivalents to the input and output distance functions (Shepherd, 1970; Coelli et al., 1998). As long as this essay takes an output maximization orientation, the index will be expressed in an output oriented approach. Therefore, in order to measure output oriented Malmquist Productivity Index, output distance function must be determined. The definition of the output distance function for each time period t is as the following:

$$d_o(x, y, t) = inf_\theta\{\theta > 0 : (x, y \ / \ t, \theta) \in T\} \text{ or} \tag{3}$$

$$d^t(x^t, y^t) = Min\{\theta : (y^t / \theta) \in P(x)\}$$

where $x \in R_N^+$ is the input vector; $y \in R_M^+$ is the output vector. t is the time and $T = \{(x, y, t) \exists x \ can \ produce \ y \ at \ time \ t$[74]$\}$.

The distance function set the smallest factor, θ by which output vector y can be produced with a given input vector x under period t's technology.

Färe et al. (1994) proposed the output-oriented Malmquist Index using distant functions in the following form:

[74] Technology frontier condition

$$M_0(x^t, y^t, x^{t+1}, y^{t+1}) = \left[\frac{d^t(x^{t+1}, y^{t+1})}{d^t(x^t, y^t)} \frac{d^{t+1}(x^{t+1}, y^{t+1})}{d^{t+1}(x^t, y^t)}\right]^{1/2} \quad (4)$$

This defines the productivity of the production point (x^{t+1}, y^{t+1}) in respect to the production point (x^t, y^t). A value greater than one will indicate positive TFP growth from period t to $t+1$. This index represents the geometric mean of two output orientated Malmquist TFP indices. The Malmquist index can be decomposed into two components: technical efficiency change (EFFCH) and technological frontier change (TECHCH), defined as:

$$M_0(y_{t+1}, x_{t+1}, y_t, x_t) = \frac{d_0^{t+1}(x_{t+1}, y_{t+1})}{d_0^t(x_t, y_t)} \cdot \left[\frac{d_0^t(x_{t+1}, y_{t+1})}{d_0^{t+1}(x_{t+1}, y_{t+1})} \frac{d_0^t(x_t, y_t)}{d_0^{t+1}(x_t, y_t)}\right]^{1/2} \quad (5)$$

where the first ratio measures the change in relative efficiency between time t to $t+1$. The geometric mean of the two ratios inside the bracket defines the shift in technology frontier between the two periods. These may be given as:

$$EFFCH = \frac{d_0^{t+1}(x_{t+1}, y_{t+1})}{d_0^t(x_t, y_t)} \quad (6)$$

$$TECHCH = \left[\frac{d_0^t(x_{t+1}, y_{t+1})}{d_0^{t+1}(x_{t+1}, y_{t+1})} \frac{d_0^t(x_t, y_t)}{d_0^{t+1}(x_t, y_t)}\right]^{1/2} \quad (7)$$

MPI is not time transitive and does not hold for circularity assumption; that is:

$$MPI_{t1,t3} \neq MPI_{t1,t2} MPI_{t2,t3} \quad (8)$$

In order to measure Malmquist Index in equation (5), we measure the distance function using DEA. The input thus employs distance functions from two different periods or technologies, $d_0^t(x_t, y_t)$ and $d_0^{t+1}(x_{t+1}, y_{t+1})$ and two pairs of input-output vectors, (x_t, y_t) and. (x_{t+1}, y_{t+1}).

2.2 Models and methods to measure the treatment (R&D subsidy) effect[75]

The term 'treatment effect' refers to the causal effect of a binary (0–1) variable on an outcome variable of scientific research or policy interest. Treatment evaluation is the estimation of the average effect of a treatment or program on the outcome of interest. That means the comparison of outcomes between treated and control observations to investigate the effect of the program on the treated group. The term has been primarily stemmed from medical literature due to measurement of the causal effect for a drug experiment or a new surgical method. However, it has been widely used in other fields of study and specifically in economics literature by pioneering work of Ashenfelter (1978).[76] There would typically be a program or treatment implemented to some group and another group would not receive that treatment.

Government programs and policies like subsidization, employee training programs and many other examples can follow treatment pattern. Inherently, there are two types of evaluation studies. The first one is control experiments such as lab experiments where the assignment into treated and control group is random. The second one is observational studies where the assignment is not random. This means certain individuals have decided to participate in the program while the others have decided not to participate. The characteristics of the participants and non-participants can be different which makes it difficult to directly compare the outcomes for those two groups. Therefore, to measure the effect of the program and comparison of the outcomes, the participants and non-participants (control) must be matched as much as possible. Selection bias also discussed in the introduction of the first chapter is the main challenge faced during treatment effect measurement, i.e. when the treated and non-treated are different with each other for other reasons than treatment status. Matching method helps to remove the selection bias before evaluating the impact of the program or treatment.

Propensity Score Matching (PSM) methodology is the approach to match treated observations with observations in non-treated control group. The first step in using PSM is to assign the observations into treated and control (non-treated) groups. Treatment D is a binary that determines whether the observation has been treated or not ($D = 1$ for treated units and $D = 0$ for

[75] The definitions and explanations are based on tutorial on treatment effect provided by MIT department of economics and the paper on 'Estimation of average treatment effects based on propensity scores' by Becker and Ichino (2002) in the Stata Journal.
[76] A first related survey has also been carried out by Heckman and Robb (1985).

control observations). The next step is to estimate a binary outcome model which is a probit or logit model for the propensity of observations to be treated based on their characteristic(s) (X).

As long as X may consist of different variables (discrete or continuous) with different dimensions, there would be a problem to match the units (dimensionality problem). This problem can be solved by introducing a single measure which is the propensity score. Propensity scores determines the probability of being treated conditional on X. The score is calculated by running a probit (or logit) regression of selection status variable D, on variables containing X. The treated and non-treated observations with closest propensity scores are matched with each other to form a counterfactual setting due to the comparison of the effect of the policy.

Propensity score matching (PSM) generates a scalar which demonstrates how good a control observation can be matched to the non-treated observation. PSM method allows to consider various control variables as matching arguments without suffering the curse of dimensionality; the more dimensions are included, the more difficult it becomes to find a good match for each treated firm. The propensity score is defined as the probability to receive a subsidy and represent a valid methodology to reduce all the dimensions considered to a single index (Rosenbaum and Rubin, 1983; Dehejia and Wahba, 2002). Matching method lumps up pre-treatment characteristics (X) into a single index variable (propensity score). The propensity score firstly defined by Rosenbaum and Rubin (1983) is the conditional probability of receiving a treatment given pre-treatment (selection) characteristics (factors):

$$p(X) \equiv \Pr\{D = 1|X\} = E\{D|X\} \tag{9}$$

where $D = \{0,1\}$ is the treatment indicator (dependent variable) and X are the observable pre-treatment characteristics which influence the likelihood of being treated (independent variables). Regarded the choice of control variables selection, variables whose participation into the treatment group does not affect them should better be included into the model (Caliendo & Kopeinig, 2008). In order to address this concern, all time-variant control variables are lagged one period with respect to the year of treatment, thus making them predetermined with respect to the treatment (Corsino et al., 2012). It is proved that in case the exposure to treatment is random within the cells formed based on dimensional vector of X, it can be considered as random also for the cells defined by mono-dimensional $p(X)$.

Now at this point, it is possible to match the observations from treated and control groups based on their propensity scores. The goal here is to find a match for each treated observations and not for control observations. Consequently, there can be control observations not used. After matching, in order to measure the treatment effect, we compare the outcomes y between the treated and control observations ($y_1\ if\ D = 1$ & $y_0\ if\ D = 0$). In treatment effect measurement, we want to compare the outcome of the treated observations with the outcome of the same observation had not been treated. As long as an observation cannot be treated and not treated at the same time, the problem of a counterfactual situation occurs. Therefore, in order to evaluate the impact of the treatment we must find a close match from the control group and compare the outcome of the treated observation with the matched non-treated observation(s) in the control group. The propensity score matching methods help us to find a close good match for treated units. For each treated observation i, PSM finds matches from observation j in the control group. Matching can be with or without replacement. The former is when each control observation can be used as a match to several treated observations, while the latter restricts each control observation not to be used more than one time as a match for a treated observation.

There are several matching methods, namely nearest neighbor (One-to-one or multiple), kernel, radius (with different calipers) and stratification. The nearest neighbor matching is the most straightforward matching technique used to match a treated observation with the observation from control group which represents the closest propensity score to the score of treated observation. In one-to-one matching the control observation is only one, while in multiple matching the treated can be matched with more than one (usually 3-nearest-neighbors) observations. Once each treated unit get matched with the control(s) unit, the average treatment effect on treated (ATT) is measured by taking the average of the differences between treated units with their matched non-treated counterparts. Not necessarily, but the nearest neighbor method is usually applied with replacement. In nearest neighbor matching all treated units will find a match. However, it is possible that these matches become fairly poor in case when the nearest neighbor has a very different propensity score. The kernel and radius matching suggest solutions to this problem of large differences in propensity scores for matched observations.

Radius matching predefines a neighborhood (equal to the radius of a circle) of propensity scores for the treated observations to be matched with an observation in the control group. The smaller the size of the radius, the higher the quality of the matches will get. However, if the radius is set to be small, then there is the probability that some treated units are not matched as the neighborhood might not contain any control observations. There should be a trade-off in setting the radius size in radius matching based on data richness and quality.

Kernel matching matches all treated observations with a weighted average of all the controls. The weights are inversely proportional to the distance between the propensity scores of treated and non-treated units. As long as kernel technique uses weighting propensity score of all related observations, it can suit the estimations related to cases with smaller number of treated in sample size.[77] Figure (1) displays a simple difference of the matching approach between nearest neighbor and kernel matching:

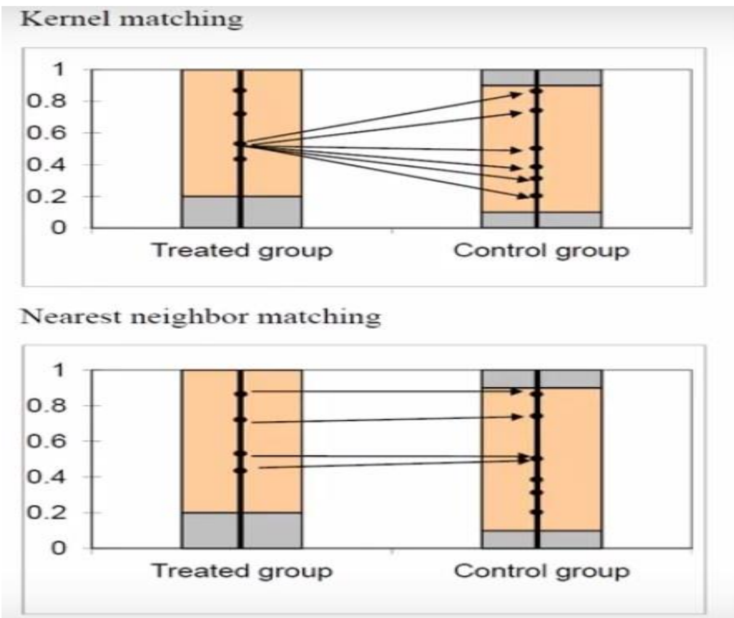

Figure 1. Kernel and nearest neighbor matching procedures

Finally, the stratification method makes divisions called as blocks based on different intervals of propensity scores such that within each block the average propensity score is the same for treated and control observations. Then, within each interval including both treated and control

[77] Another method introduced to deal with the odds of treatment and unbalanced design with few treated units and many controls is Oaxaca-Blinder estimator developed by Kline (2011). The O-B estimator, despite allowance for negative weights carries out straightforward computation of standard errors. The method is based on the works of Ronald Oaxaca (1973) and Alan S. Blinder (1973) who proposed a propensity score reweighting estimator based upon a linear model for the conditional odds of being treated—a functional form that emerges, for example, from an assignment model with a latent log-logistic error.

units, the average treatment effect (ATT) is the average of the ATT for each block with weights given by the distribution of treated units across the blocks. However, discarding the blocks which do not possess any treated and/or controls is one drawback of stratification method. The nearest neighbor method already defined, does not expose this problem. In the following, the formal descriptions and formulations of the propensity score matching methods discussed previously are provided.

Let T be the set of treated observations and C the set of control observations. Y_i^T and Y_j^C are the observed outcomes of the treated and control units as well. Nearest neighbor matching is defined as the following:

$$C(i) = \ min_j \left\| p_i - p_j \right\| \tag{10}$$

where $C(i)$ is the set of control observations matched to the treated observation i with a value of propensity score p_i. p_j is the estimated propensity scores for control observations. $C(i)$ is a singleton set unless there are multiple nearest neighbors which rarely happens particularly when the set of characteristics X includes continuous variables.

The radius matching formulation is almost the same except there is a radius r which predefines a maximum distance for the possibility of treated units to be matched with controls.

$$C(i) = \ \left\langle p_j \middle| \left\| p_i - p_j \right\| < r \right\rangle \tag{11}$$

In radius matching all the control observations with estimated propensity scores falling within a specified radius r from p_j are matched to the treated unit i.

In kernel matching each treated observation i is matched with several control observations (js) by weights inversely proportional to the distance between treated and control observations. The weights are defined as the following:

$$w(i,j) = \frac{K(\frac{p_j - p_i}{h})}{\sum_{j=1}^{n} K(\frac{p_j - p_i}{h})} \tag{12}$$

where K(.) is the kernel function[78], p_j is the propensity score for the control observation, p_i is the propensity score for the treated observation and h is the bandwidth parameter for the kernel function. In the numerator we have the kernel of the division of the distance between propensity scores of the treated unit and the single matched control unit $(p_j - p_i)$ and a predefined bandwidth (h), while the denominator is the sum of these kernel values for all the control matched units. This proportion provides the weights for each control matched unit to be used in measuring the treatment effect.

In stratification matching the outcomes are compared across intervals or blocks used for matching treated with controls. The ATT will be measured using the average of the difference of propensity scores within each block.

The four PSM methods discussed undermine different tradeoffs between quality and quantity of the matches and none of them is ex ante superior than the others. However, applying them together will help in carrying out robustness check.

Another noticeable issue in matching techniques is the term common support which is used to restrict the matching based on a common range of propensity scores for the treated and control observations. For instance, we can consider a situation in which the maximum propensity score measured for treated observations is higher than the one for control group (e.g. 0.9 for treated and 0.8 for control observations) or a situation in which the minimum propensity score for control observations is lower than the one for treated observations (e.g. 0.2 for treated and 0.2 for control observations). In case the matching gets limited to be carried out for treated observations with propensity scores not higher than a predefined score (e.g. 0.8) or for control observations with propensity scores not lower than a predefined score (e.g. 0.2), then the common support ranges between 0.2 and 0.8 (%20 and %80 of probabilities) and the PSM matching technique will be carried out in this limited range. PSM can restrict the sample to common support region by defining a tolerance limit which determines the bandwidth for matching treated and controls as shown in the following Figure (2):

[78] Kernel function can be in the forms of Gaussian kernel or Epanechnikov kernel.

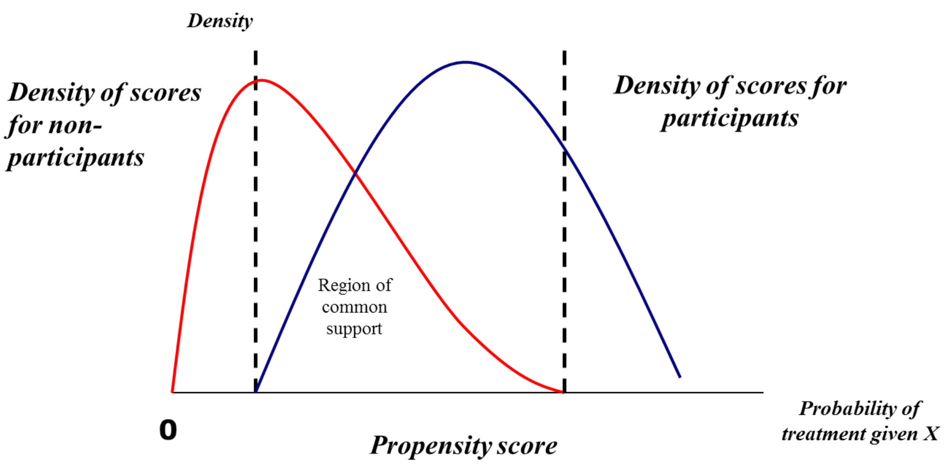

Figure 2. The probit distributions of treated and non-treated observations to identify propensity scores

The quality of the matches can improve by imposing common support restriction. However, as long as some high quality matches can be ignored in the common support boundaries and the sample shrinks as well, this improvement of the matching quality using common support option is not per se (Lechner, 2001).

At this point after the matches are found for the treated observations, we can measure the average treatment effect (ATE). Average treatment causal effect is simply evaluated by the measuring the difference between the outcomes of treated and control observations. ATE is defined as the following:

$$ATE = E[Y_{1i} - Y_{0i}] = E[Y_{1i}|\, D_i = 1, X] - E[Y_{0i}|D_i = 0, X] \tag{13}$$

where Y_{1i} is the outcome of treated unit, Y_{0i} is the outcome of non-treated unit, D_i is the binary treatment variable and X is the vector of characteristics of the observation. If the treatment happens randomly, then ATE simply compares the average outcomes between treated and control observations to measure the treatment effect. However, for the situations in which the unit or observation can self-select to participate in treatment or the case in which there is selection between participants to be treated, the experiment is not random and treated and control observations are not similar. This leads to a bias in measuring the ATE.

In order to tackle this bias, we use average treatment effect on treated ($ATET$) as the following equation, which is the difference between outcomes of the treated observations and the same treated observation had not been treated.

$$ATET = E[Y_{1i} - Y_{0i}|\, D_i = 1, X] = E[Y_{1i}|\, D_i = 1, X] - E[Y_{0i}|D_i = 1, X] \tag{14}$$

The second term cannot practically happen in real world as a unit cannot be treated and not treated at the same time. Therefore, the second term is counterfactual and needs to be estimated. In order to estimate the second term in $ATET$, we can substitute a non-treated control observation matched with the treated observation. The match is carried out based on the observable characteristics of the observations. Propensity Score Matching (PSM) explained previously, finds this match by using a singleton propensity score for treated and control observations. Consequently, after matching on propensity scores $ATET$ can be defined as:

$$ATET = E[Y_{1i} - Y_{0i}|D_i = 1, p(X)] = E[Y_{1i}|\, D_i = 1, p(X)] - E[Y_{0i}|\, D_i = 0, p(X)]$$

where $p(X)$ is the propensity score of the treated and control observations measured using one of the four methods already defined. Finally, after that each treated observation i is matched with j control observations the $ATET$ is empirically measured as the following:

$$ATET = \frac{1}{n} \sum_{i \forall D_i = 1} \left[y_{1i} - \sum_j w(i,j) y_{0j} \right] \tag{15}$$

where w are the weights calculated and given to each match (in case of one-to-one nearest neighbor ($w(i,j) = 1$). In case of kernel matching we will use all the y_0 for all of the control observations with the corresponding weights ($w(i,j)$). It is worth to consider that the average treatment effect on treated ($ATET$) is being measured only for treated observations ($D_i = 1$).

However, like many other econometric methods, treatment effect measurement using PSM binds to some assumptions. The first assumption is the independence of outcomes and treatment. For random experiments, the outcomes are assumed to be independent of the treatment ($y_0, y_1 \perp D$). This means treatment is not decided based on the outcome we are measuring. For observational studies, the outcomes are independent of treatment conditional on $X (y_0, y_1 \perp D|X)$. In the other words, the key assumption in PSM is that treatment is independent of the outcomes conditional on X_i which means unobserved variables do not affect the treatment status:

$$E(Y_i|\ D_i = 1, X) = E(Y_i|D_i = 0, X) \quad (16)$$

This means the treatment variable is exogenous. Matching suits when conditional independence assumption holds and the study has a detailed information on the selection process. The assumption considers Y and D are stochastically independent conditional on treatment decision observables (X).

A weaker assumption than the conditional independence known as unconfoundedness assumption assumes the treatment and control group outcome are independent conditional on X $(y_0 \perp D|X)$. The identification of the treatment effect is conditioned on unconfoundedness assumption according to which the treatment D_i is independent of the potential outcomes Y_{0i} and Y_{1i}, conditional on a set of variables X. [79]

The next assumption to be hold in order to carry out the PSM method, is balancing pre-treatment variables given the propensity score $p(X)$ $[balancing\ hypothesis: D \perp X|\ p(X)]$. If $E[D_i|X_i]$ is a function of X_i, matching estimator would be the option to measure the effect of the treatment. The next computational challenge is how to find good matches for each values of covariates vector to form a reliable sample for non-treated. As proved by Rosenbaum and Rubin (1983), in case conditioning on X_i, eliminates selection bias, thus conditioning on $P[D_i= 1|X_i]$ would do the same. If balancing hypothesis is satisfied, observations with the same propensity scores must have the same distribution of observable (and unobservable) characteristic independent of the treatment status. This means for a given propensity score, exposure to treatment is random, consequently the treated and control units are on average identical.[80] Propensity score can be estimated using any standard probability function in $\Pr\{D_i = 1|X_i\} = \phi(h(X_i))$, where $\phi(.)$ is the normal (or logistic) cumulative distribution and $h(X_i)$ is a function of covariates. $h(X_i)$ is specified due to satisfying the balancing hypothesis.

The final main assumption to be noted in treatment effect analysis is the Stable Unit Treatment Value Assumption (SUTVA) (Rubin, 1973). It assumes that the outcome of one observation (firm in our case) is not affected by treatment assignment to any other observation, i.e.

[79] The assumption that probability of being included into the treatment is greater than zero given any set of covariates (overlapping): Prob(D=1|X=x) ϵ (0,1) has to hold as well. (This is one of two identification assumptions)

[80] Or the assignment to the treatment is independent of the X characteristics given the same propensity score.

the treatment does not indirectly affect the control observation. This assumption holds when the spillover is negligible or can be assumed away. Therefore, there is no general equilibrium effect which takes into account spillovers effect. The relaxation of this assumption represents one main difference between structural models and matching approach.[81]

3. *Empirical Strategy and models implications*

Previous section has reviewed the models and approaches to measure total factor productivity change in terms of efficiency change and technical frontier change, besides methodologies to evaluate the impact of subsidies on TFP measures. This section explains the empirical implication of these methods. DEA-based Malmquist Index has been used to measure the TFP and the decomposed elements for enterprises. DEA as a non-parametric method applies data on input(s)/output(s) for homogenous DMUs to measure the relative efficiency measures based on the best performers frontiers. The measures of efficiency will be calculated *for each different sector*, which satisfies DEA's requirement for homogenous process of productions for enterprises. One advantage of DEA is taking no pre-assumption on production function while measuring relative efficiency of the firms in a specific sector (such as service, construction or IT-related sectors) in which the production function contains different parameters than manufacturing sector. Moreover, DEA does not require price information and only applies the quantities for inputs and outputs.

STATA software is used in order to empirically estimate the Malmquist Productivity Index components. Lee et al. (2011) has proposed a user-written command 'malmq' in STATA Chicago Conference, which enables STATA to estimate productivity using DEA frontier analysis codes proposed by Ji and Li (2010). As long as the command and framework is based on simple input or output oriented constant return to scale (CRS) DEA, our empirical strategy keeps up with CRS DEA model definition.

R&D subsidies are allocated mainly to private firms (and not public provincial entities), hence, the output (profit) maximization suits better than a cost minimization approach. Consequently, the output-orientated CRS DEA (equation 4) is the model applied to measure the relative efficiency and the technological frontier.

[81] Next chapter relaxes this assumption and estimates a model in which spillover effect is also considered.

In order to implement the Malmquist DEA method, input variables (x_i) and output variables (y_r) for all DMU j s are determined as the following. Referred to most important production factors in economic theory (labour and capital), the model takes number of employees (the proxy for labour), moving average of tangible fixed-assets (the proxy for capital stock and capital) and intermediate inputs (the proxy for other factors contributing in production), as the input variables. Total revenue is the variable taken into account as the proxy for the output. Subsequently, The model is applied for three inputs and one output. As a rule of thumb, the number of DMUs (n), should be more than three times of the sum of inputs and outputs ($t + m = 1 + 3 = 4$) to obtain an effective distinguishing power (Cooper et al., 2007). As will be shown in the section related to data description, the number of DMUs for each analysed sector or for all pooled DMUs is sufficiently more than 12.

The Data on inputs and output for each firm (DMU)-year observation is extracted from the data on financial statement and balance sheet of private firms (for each single year from 2007-2014) provided by AIDA[82]. AIDA is the Bureau van Dijk's product on company information related to Italy which contains firm-level data about one million companies. The data on inputs/output variables will be applied in measuring the Malmquist Index over time for consecutive years to realize the relative efficiency and technical frontier changes. time period (7 years) to extract the data is based on the data availability and the setting for short-run or long-run effects. The Malmquist Index generates measures of TFP change and TFP decomposed elements of technical frontier change and efficiency change for each year.

These measures are used as the outcome variables to measure the impact of the public R&D subsidies (treatment binary variable). Data on R&D subsides is extracted from APIAE's dataset provided by ISPAT office for the grants allocated to firms at each year from 2001 to 2013. Treatment variable is actually the R&D subsidy instalment, province of Trento has allocated to an R&D project in a specific year (Between 2001 to 2013). Therefore, the common time interval of data availability for both subsidies and TFP measures will be between 2007-2013. This time interval can be extended for subsidies left to 2001 and for TFP measures right to 2014.

In this section as previously discussed, the criteria and the evaluation procedures to allocate R&D subsidies are assumed observable. Therefore, Propensity Score Matching (PSM) which

[82] Italian company information and business intelligence: In Italian (Analisi Informatizzata delle Aziende Italiane)

controls for observables can be effectively applied. Our data satisfies the PSM requirement for good quality data on control variables and binary treatment variable. Nearest-neighbour (one-to-one neighbour) and Kernel PSM techniques are applied to measure the effect of R&D subsidies on TFP change. PSM generates the propensity scores based on the covariates vector or control variables X_i which matches two (or more) observations, balancing the characteristics of the firms. X_is are the observable factors influencing the selection procedure. *Size, age of the firm and the sector* are the factors chosen as the controls. Size of the enterprise usually stands as a main criteria in allocating not only R&D subsidies to an entity but also many other types of treatments as noted in the literature. The industrial policies pay much attention to the size as one of the main firm's characteristics. The policy makers usually customize the subsidies decision based on the size of the enterprise (if the corporation is micro, an SME or a large firm). Referred to the previous section related to matching method description, the control variables must demonstrate their pre-treatment values as the decision to support an R&D project is simply taken based on the pre-treatment characteristics. Therefore, the observable controls are lagged at least one year preceding to the subsidy allocation time.

Table (1) supports the selection of the size as a control independent variable because subsidy rates allocated to different types of R&D projects directly depend to the size of the firm. Year of foundation (firm age) is another influential factor in decision on allocation of R&D subsidies. The age of an R&D doing firm proxies for the experience in carrying out the innovation projects. Despite the policy is focused on supporting younger firms to do R&D, age can represent the reputation of a firm which can persuade the policy maker to trust a firm's proposal to carry out R&D. Sector or industry in which the firm operates can be another important factor affecting evaluation and selection process, as LP 6/99 provokes the province to invest more in IT-related industries based on the ICT development horizon emphasized in European Union strategy design and the regional priorities.

Being affected by other firms' spillover can be captured in efficiency change and/or technical frontier change. However, as previously explained the study deals with the direct relationship of R&D subsidies on target variables without opening the black box. In empirical estimations we assume SUTVA is not violated.[83] Furthermore, matching method assumes there

[83] This assumption gets relaxed in the next chapter.

are no unobservable factor affecting the selection process[84]. Theoretically,[85] the evaluation process has clear straightforward criteria to select firms for R&D subsidies, hence we can assume the unobservable factors do not significantly influence the selection process. Therefore, the PSM matching technique is capable to provide answers to our H.1_H.4. We have to emphasize that empirical implementations are discussed more in detail in each section related to the results

At this point, we have explained the empirical procedures of the current essay to generate results for investigation of the research hypotheses. However, before discussion on the results relevant data and variables related to the aim of the research will be described and discussed in the following section.

4. Data and variables

This section reviews the data and variable used to evaluate the effect of R&D subsidies on TFP change. In line with the empirical strategy related to the methodologies used for treatment effect analysis (previous section), the steps and procedures to frame the final dataset applied to estimate the treatment effect are completely explained in Appendix (3.b). Moreover, the primary variables and data extracted by this procedure for all the population of active firms in the region will be described in appendix (3.c).

4.1 Data and variables related to public R&D subsidies

R&D subsidies data relates to APIAE's dataset for the grants allocated to firms at each year from 2001 to 2013. This dataset is provided by ISPAT office. There are in total 600 observations (grant allocations) for each firm(project)-year. As long as the analysis is at firm(project)-year level, similar firm being granted in two or more years, is considered as a different observation. The original dataset consists of the unique fiscal code of the enterprise[86], application code, application date, grant installment date, installment code, type of the project, total planned expenditure of the project, total evaluated expenditure of the project, evaluation

[84] A method to relax this assumption is conditional difference-in-difference (CDID) discussed in first chapter (See Smith and Todd (2005)).
[85] This might not hold in practice, as there are possibilities for unobservable factors influencing the R&D subsidies allocation.
[86] Codice Fiscale (In Italian)

method of subsidy allocation, the contribution to the project, size of the subsidized firm and geographical place in the region.

Figure (3) illustrates the frequency of the grants allocated to firms for R&D projects at each year for the period 2001-2013. The first only one installment happens in 2001, while in 2002 there are just three installments in total as well. The number of subsidies experiences two consecutive highly increase in 2003 and then in 2004, to 18 and 38 subsidies, respectively. The number of subsidies remains around 40 in the next four years except for 2006 which decreases to 24 supported projects. Number of subsidies grows rapidly in 2009, 2010 and 2011 reaching to 89 subsidy allocations. Year 2012 represents the highest number of subsidy assignments (153 subsidies) demonstrating a 71% growth in subsidies frequency in comparison with the previous year. Year 2013 shows a really low amount of subsidies with 40 installments because the data on all the installments have not been completely reported[87].

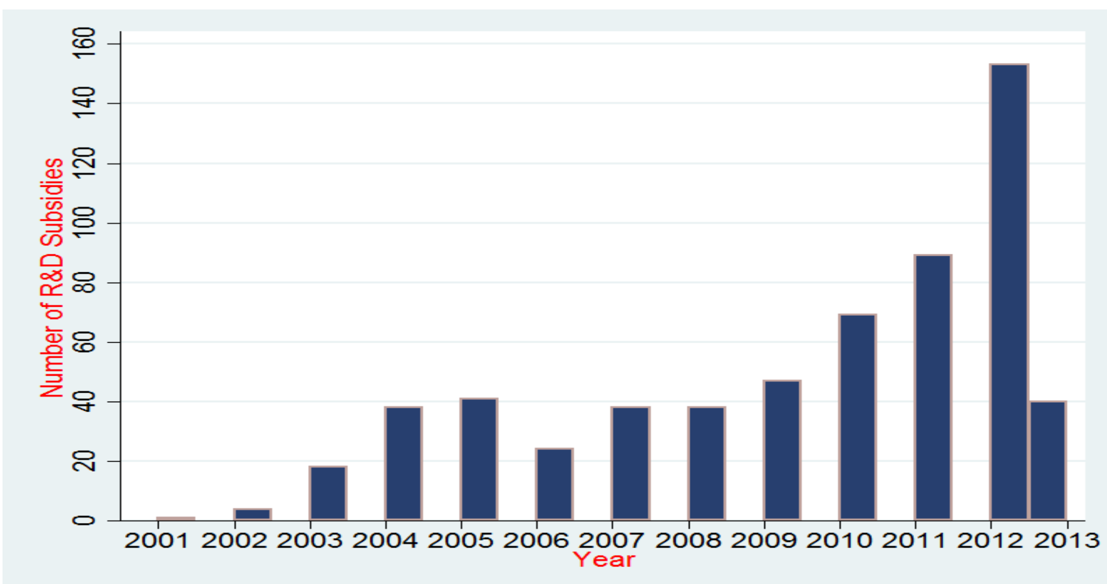

Figure 3. Number of subsidies allocated to projects each year (2001-2013)

In the following, table (2) illustrates some statistics about the total amount of planned R&D expenditure, actual R&D expenditure and the public contribution to the projects. The amount for estimated accepted actual R&D expenditures are slightly lower than the total planned expenditures.

[87] The last registered installment in 2013 dates back to July 2013.

The former represents the amount which public agency expects to occur, while the latter is the amount which private enterprises have planned and claimed to spend on R&D. This shows that public agency has modified the planned expenditure after reviewing the projects. The standard deviation shows the amount of R&D private expenditure and R&D subsidies can differ largely between various projects.

Table 2. Descriptive statistics for R&D expenditures (Investment by firms and public subsidies)

R&D Expenditure	Mean	Standard Deviation	Min	Max
Total Planned	1,210,163.59	1,662,327.60	36,744.33	16,260,000.00
Actual Accepted Amount	1,049,607.50	1,507,223.33	0.00	16,210,000.00
Public Contribution	583,025.06	966,564.26	0.00	12,035,000.00

Source: Elaboration on APIAE data (All numbers are in Euro €)

The applications for subsidies are screened by different evaluation procedures known as automatic, evaluative and negotiation procedures. These procedures themselves consist of other categories. Table (3) shows the distribution of these three general types of evaluation procedures together with the procedures each type includes.

4.2 Data and variables related to outcome TFP measures and firms' characteristics for subsidized and non-subsidized firms

The data on entities in the province comes from Aida[88] dataset which is the Bureau van Dijk's product on company information for Italy. Aida covers firm-level data about one million companies. In this study, the basic primary dataset extracted from the Aida database includes information for 5,506 enterprises operating in Trento province for 7 years from 2007 to 2014. This shapes a balanced dataset with 44,048 observations at firm-year level. Not surprisingly, the dataset contains missing values for different variables in which we are interested to carry out our analysis.

However, it will be polished and cleaned before running the related analysis. As mentioned, the whole procedure aiming to the construction the final dataset to estimate the treatment effect is provided in appendix(3.b). In the following, table (4) reviews the variables used in order to

[88] Italian company information and business intelligence: In Italian (Analisi Informatizzata delle Aziende Italiane)

measure the Malmquist TFP change measures and some extra variables of interest related to the our sample of the firms. *Our sample as discussed in the appendix, relates to the firms in industries in which grant allocation happens at least once in the period of analysis. At the same time, these are the firms which the data used to measure TFP measures have been provided for seven consecutive years.* All non-subsidized firms are the firms which have the capability to ask for R&D subsidies and in general those who can do R&D. Referred to section 1.3, *all the firms operating in the province of Trento are eligible to apply* for the subsidies by submission of a project to the province.

Table 3. The number of subsidy allocations based on the evaluation method by the public agency

Type of Evaluation	***Categories***	***Number of subsidies assigned by each evaluation type***	***Share of total subsidies***
Automatic	*AUTOMATICA*	*127*	
	BANDO 1/2008 – RIC	*44*	
	BANDO 5/2009 – RIC	*32*	
	BANDO 6/2009 – RIC	*22*	
	BANDO 2/2010 – RIC	*37*	
	BANDO 2/2011 – RIC	*15*	
	Total	*277*	*46%*
Evaluative	*VALUTATIVA*	*284*	
	RICERC VALUTATIVA	*3*	
	VALUTATIVA CONGIUNTA	*8*	
	VALUTATIVA con DEROGA	*16*	
	Total	*301*	*50%*
Negotiation	*NEGOZIALE*	*7*	
	NEGOZIALE CONGIUNTA	*5*	
	Total	*12*	*4%*
All Methods	*Total*	*600*	*!00%*

Source: Elaboration on APIAE Data

Table 4. Descriptive statistics of variables used in Malmquist DEA model and other variables of interest

	Subsidized				Non-Subsidized			
Variable	Mean/Median	Std. Dev.	Min	Max	Mean/Median	Std. Dev.	Min	Max
Number of Employees	149	212.25	3	1212	46	131.4297	1	5342
Intermediate Inputs[*]	39338.6	96294.28	77.847	496991.9	12222.58	35752.13	7.068	556953.3
Average Fixed Asset	8272.05	10841.07	0.5405	47429.5	5434.08	45086.81	0.27	1110105
Revenue (Sales)	49369.01	110535.7	106.346	598582.7	15124.14	41271.55	2.041	676495.2
Age	23.90	15.76	2	64	31.7514	31.19961	1	208
Number of Recorded Subsidiaries	5	6.090486	0	19	2	3.14425	0	31
Number of Companies in Corporate Group	15	42.10086	0	352	18	117.6021	0	1486
Number of Directors	9	7.686614	1	39	7	6.615148	1	40
Total Assets[≈]	46000.51	70968.38	111.322	324900.5	16261.41	62517.23	42.827	1388085
Total Inventory[≈]	8164.2	20499.06	0	153852	2634.295	7077.453		137995
R&D[**] Expenditure[≈]	427.2358	1053.635	0	4734.744	28.0895	244.7339	0	6343.516
Expected R&D Spending[≈]	1303673	1430202	0	6398674	_	_	_	_
Total Subsidies[≈]	624093.5	717576.5	0	3000000	0	0	0	0
Observation Freq.		111				4040[***]		

* The intermediate inputs includes the raw material and the service applied for production.

** Because of lack of precision and not available data for R&D spending, the R&D Expenditures is summarized for 85 treated and 2.600 non-treated enterprises. ***Data is summarized for years 2008 to 2014. [≈] amounts are in thousands Euros €

The grants can be applied at any time and there is no deadline to submit a project. However, the projects are evaluated by time order they have been submitted. Moreover, it is worth to restate that in this chapter the fixed R&D cost is assumed to be zero. All this lead to forming our control group. Surprisingly, the average larger firms have received subsidies *more frequently* for the period between 2008 to 2013. However, as expected younger firms has higher rate for subsidies contributed (with respect to the amount of the project).

The dataset of *total 4,151 firm-year observations* (balanced dataset of 593 firms for 7 years), contains *4040 non-subsidized and 111 subsidized observations* (table (4)). Based on the input and output indices, TFP measure is calculated using Malmquist DEA method (Equation 5) explained in previous section. Table (5) categorizes these total 4,151 firm-year observations (593 firms) into subsidized and non-subsidized firms based on the industry sector. In order to classify firms in different sectors, we have elaborated to change ateco 2007 economic activity 6-digit industry codes into main sectors of activity. As long as ateco 2007 codes based on first digits overlap across different sectors, the process related to this transformation is explained in appendix (3.d)

Table 5. The frequency of observations (all, subsidized and non-subsidized) based on industry

Sector	Total Observations	No. of Firms	Subsidized Obs.	Non-subsidized Obs.
MANUFACTURING	1316	188	71	1245
CONSTRUCTION	700	100	5	695
WHOLESALE AND RETAIL TRADE; REPAIR OF MOTOR VEHICLES AND MOTORCYCLES	1428	204	3	1425
INFORMATION AND COMMUNICATION	364	52	23	341
PROFESSIONAL, SCIENTIFIC AND TECHNICAL ACTIVITY	343	49	9	334
TOTAL	4151	593	111	4040

As previously pointed out, one input applied in calculating the TFP measures, is moving average fixed asset as a proxy for capital. In order to measure the input for year 2007, we need the data on fixed asset for year 2006 not available in our original dataset. Therefore, we cannot measure this input index and consequently Malmquist TFP measures for year 2008. Table (6) describes the TFP change and TFP components over the time. This is the reason we see lower number of observations in table (6) in comparison with table (5) i.e. the subtraction of 593 observations from total 4,151 observations which *equals 3457 (593 firms for 6 consecutive years)*. Obviously, there are 10 R&D subsidies allocation related to year 2008, which makes the total number of treatments 101 (10 less than 111 total allocations). However, we can still take into account the treatments occurred in 2008 in effect evaluation as long as there is a minimum lag of one year between the time treatment and the outcome are measures.

The measurement of the effect of R&D subsidies on TFP measures is estimated by comparison the outcome variables of treated and non-treated firms within each industry. In other words, we match the treated firms and control firms within each industry or inside sectors with similar technological intensity. Therefore, the TFP measures are statistically described in table (7) for industries which we carry out the treatment effect analysis (The five industries in which at least one subsidy allocation occurs).

The highest subsidies assignment frequencies belong to manufacturing and information technology (IT) industries with 65 and 21 treatments, respectively. Manufacturing sector, construction sector and wholesale and retail (repair of motor and motor cycles) sector are assumed as medium and low technological industries, while IT and professional scientific and technical activity sectors are considered as high technological sectors. The subsidies frequencies in low-medium technologies count up to 72, while the frequency is 32 treatments for high technology sector.

Size is one important main factor, both in the theoretical background regarded the relationship between R&D activities and TFP growth and in empirical aspect regarded to the allocation of subsidies to R&D projects. Table (8) compares the treated and non-treated TFP outcome measures for firms based on different number of employees (if the firm is small medium sized (SME) or large) for the sample. The number of larger firms is not surprisingly lower than SMEs (23 vs. 570 firms).

Table 6. Descriptive statistics of outcome TFP measures for subsidized and non-subsidized enterprises for each year

	Treated (Subsidized)				Non-treated (Control)				Total Obs.
Year	tfpch†	effch††	techch†††	Freq.	Tfpch	effch	Techch	Freq.	Freq.
2009	0.94*	1.28	0.77	11	1.44	1.37	0.96	582	593
	(0.27)**	(0.44)	(0.18)		(8.86)	(5.33)	(0.24)		
2010	1.05	0.91	1.29	19	1.07	1.17	1.03	574	593
	(0.22)	(0.35)	(0.46)		(0.96)	(1.55)	(0.37)		
2011	1.09	1.10	1.02	22	1.08	1.07	1.03	571	593
	(0.35)	(0.34)	(0.18)		(0.93)	(0.90)	(0.23)		
2012	1.04	0.88	1.22	39	1.26	1.19	1.10	554	593
	(0.33)	(0.32)	(0.22)		(5.31)	(5.06)	(0.21)		
2013	1.03	1.15	0.92	10	1.10	1.06	1.06	583	593
	(0.11)	(0.22)	(0.15)		(1.13)	(0.84)	(0.27)		
2014	_***	_	_	_	1.10	1.05	1.05	593	593
					(1.16)	(0.83)	(0.19)		
Total	1.04	1.00	1.11	101$^{\Delta}$	1.017	1.15	1.04	3,457$^{\Delta}$	3,558
	(0.29)	(0.36)	(0.31)		(4.29)	(3.11)	(0.26)		

† Total factor productivity (TFP) change †† Efficiency change ††† Technological change

* The intermediate inputs includes the raw material and the service applied for production.

** Because of lack of precision and not available data for R&D spending, the R&D Expenditures is summarized for 85 treated and 2.600 non-treated enterprises. ***Data is summarized for years 2008 to 2014.

Table 7. Descriptive statistics of outcome TFP measures for subsidized and non-subsidized enterprises based on sector of activity (according to ATECO 2007 classification: See Appendix 3.d)

Industry	Subsidized				Control			
	Tfpch	Effch	Techch	Freq.	Tfpch	Effch	Techch	Freq.
MANUFACTURING	1.044	1.004	1.133	65	1.012	1.047	1.033	1063
	(0.305)	(0.378)	(0.335)		(0.243)	(0.343)	(0.294)	
CONSTRUCTION	1.214	1.287	1.004	4	1.565	1.541	1.112	596
	(0.395)	(0.651)	(0.166)		(5.493)	(5.279)	(0.402)	
WHOLESALE AND RETAIL TRADE; REPAIR OF MOTOR VEHICLES AND MOTORCYCLES	1.013	1.029	0.987	3	1.007	1.00	1.008	1221
	(0.0522)	(0.100)	(0.059)		(0.106)	(0.118)	(0.071)	
INFORMATION AND COMMUNICATION	0.988	0.962	1.034	21	1.033	1.012	1.027	291
	(0.268)	(0.288)	(0.104)		(0.282)	(0.269)	(0.123)	
PROFESSIONAL, SCIENTIFIC AND TECHNICAL ACTIVITY	1.098	0.975	1.239	8	1.828	1.527	1.060	286
	(0.259)	(0.273)	(0.523)		(12.636)	(7.614)	(0.320)	
TOTAL	1.043	1.005	1.111	101	1.175	1.153	1.040	3457
	(0.292)	(0.360)	(0.313)		(4.298)	(3.111)	(0.259)	

† Total factor productivity (TFP) change †† Efficiency change ††† Technological change

SMEs show a higher frequency in receiving R&D grants in comparison with their larger counterparts in the sample. This is not in contrary to table (4) in which the mean of number of employees was smaller for subsidized firms with respect to non-subsidized, as long as the means there are still lower than the maximum limit of number of employees for being an SME (250 employees).

At this point and after descriptive analysis, the estimation of the effect of R&D subsidies on TFP measures will be implemented for different diverse possible settings. However, the next section focuses only on the main part of our results.

Table 8. Descriptive statistics of outcome TFP measures for subsidized and non-subsidized enterprises based on the size (SME or Large firm)

	Subsidized				Non-Subsidized				Total Obs.	No. of firm
Size	Tfpch†	Effch††	Techch†††	Freq.	Tfpch	effch	Techch	Freq.	Freq.	Freq.
SME	1.049	1.007	1.108	82	1.180	1.157	1.040	3338	3420	570
	(0.320)	(0.363)	(0.305)		(4.373)	(3.165)	(0.261)			
Large	1.015	0.995	1.125	19	1.035	1.042	1.022	119	138	23
	(0.116)	(0.358)	(0.355)		(0.249)	(0.255)	(0.205)			

† Total factor productivity (TFP) change †† Efficiency change ††† Technological change

5. *Empirical Analysis and Results*

The previous sections discussed the methodologies and data and variables used by them to generate TFP change and its components of efficiency change and technological (technical frontier) change in the first step and to measure the impact of R&D subsidies allocation on TFP measures as the targeted outcome in the second step. In order to evaluate the effect of subsidies, we use propensity score matching (PSM) explained in section 2.2. As discussed in empirical strategy section, the PSM in order to estimate the treatment effect on outcome, matches subsidized firms with control non-subsidized enterprises which are the most similar based on observable characteristics. These characteristics are variables which influence the selection process and the outcome. However, this may lead to a bias in capturing the estimated effect. PSM method reduces the bias by conditioning the probability of being subsidized on observables.

In this study, PSM will be carried out for different settings. The effect evaluation is implemented for two main industries (manufacturing and IT) in which the frequency of R&D subsidies allocation is much higher in comparison with other industries (table (7)). Moreover, the technique will be run for two different groups of sectors based on technological intensity (low-medium tech and high-tech sectors). Finally, the matching process will be executed based on the subsidization evaluation methods. Moreover, the effect is measured for the whole observations in all five industries with at least one treatment occurrence.

In order to proceed the measurement of the effect, balancing property must be satisfied before matching the subsidized with control for all estimations. This results in generation of propensity scores for each unit to be used for matching procedure. Hence, balancing property satisfaction is investigated for each of the analysis setting and propensity score graphs for subsidized and control units are generated as well. Propensity scores in each analysis setting will be recorded to be used in the propensity score matching. After all, average treatment effect on the population (ATE) and average treatment effect on the treated (ATET) are measured using nearest neighbor and kernel matching techniques. Standard errors are further reported in all estimations. After treatment effect measurement, the balancing of propensity scores for treated and untreated based on each observable covariate will be shown as well.

The outcome dependent variables are total factor productivity change (tfpch), and the decomposed elements of TFP; efficiency change (effch) and technological change (techch). The observable independent variables discussed previously, are pre-treatment size and pre-treatment age of the firms. Industry effect is controlled while measuring the effect through each sector or sector classifications.

Although measuring and reporting all the impact measures will be a long process, we report all effect measures and it is just one table in which the significant effects are reported. Moreover, balancing properties satisfaction and propensity score (box and kernel density) graphs and summaries will be mainly described in the related appendices (3.e through 3.j) except for some cases which are mentioned in the main text for exemplification of the results. The impact of R&D subsidies on TFP measures (Malmquist DEA productivity indices) is evaluated using PSM method applying the balanced panel datasets in user-written algorithm in STATA. New version of STATA14 suggests commands to run matching process including PSM method. [89] The PSM procedure proposed by Becker and Ichino (2002) and the propensity score graphs by Leuven and Sianesi (2003) are applied as well.

[89] Codes and .do files scripted to construct panel dataset and datasets used can be provided abiding to privacy issues.

5.1 R&D subsidies impact evaluation based on industry (manufacturing and ICT sectors): PSM method

This section estimates the average treatment effect of public R&D subsidies on outcome TFP measures for the whole population (Average treatment effect: ATE) and for subsidized units (Average treatment effect on treated: ATET) in manufacturing and ICT sectors. In order to estimate the effect of R&D subsidies, treatment effect analysis using propensity score matching method based on Abadie & Imbens (2006, 2012), including nearest neighbor (NN) and kernel estimators will be implemented.[90] It is assumed that matches for each treated unit is searched within controls in the same sector.

However, before estimating the effect of R&D subsidies on TFP change, balancing property satisfaction and propensity scores are checked and generated for each industry. The balancing property is checked for all five industries with at least one treatment. The balancing is satisfied for two main sectors of manufacturing and ICT within which treatment effect analysis is carried out. The property is not satisfied for construction and wholesale retail, while it holds for scientific and technical activity sector. The detailed procedures of testing balancing property can be found in appendices (3.e and 3.f). Moreover, the propensity graphs for manufacturing and ICT are also illustrated (appendix 3.g). The following table (9) shows the average of propensity scores for each sector which at least one grant allocation happens after balancing property satisfaction is investigated. As long as balancing of observations for treated and untreated takes pre-treatment observables, year 2008 is excluded and the number of subsidized and non-subsidized observations include the observations after 2008.

In table (9), not surprisingly, the average probability of receiving a grant is higher for subsidized firms in comparison to control units in all industries. As long as the number of R&D subsidies are scant in three out of five sectors, to increase the estimation precision and effectiveness, treatment effect evaluation is carried out first for two main industries (manufacturing and ICT) with the highest frequencies of subsidies assignments and second for groups of industries shaping low-medium tech and high tech industries.

[90] teffects psmatch (PSM treatment effect estimator), attnd (Nearest neighbor (one-to-one) estimator) and attk (Kernel estimator) are all used for our analysis to check for robustness.

Table 9. descriptive statistics for propensity scores by sector of activity

INDUSTRIES		Subsidized Pscore	Freq.	Control Pscore	Freq.
Low-medium Tech Industries	MANUFACTURING	0.087*	65	0.0554	1063
		(0.092)**		(0.042)	
	CONSTRUCTION	0.0078	4	0.006	596
		(0.0005)		(0.005)	
	WHOLESALE AND RETAIL TRADE; REPAIR OF MOTOR VEHICLES AND MOTORCYCLES	0.002	3	0.002	1221
		(0.0003)		(0.001)	
High Tech Industries	INFORMATION AND COMMUNICATION	(0.147)	21	0.060	291
		(0.183)		(0.056)	
	PROFESSIONAL, SCIENTIFIC AND TECHNICAL ACTIVITY	0.029	8	0.027	286
		(0.006)		(0.007)	
	TOTAL	0.041	101	0.027	3457
		(0.031)		(0.022)	

* mean **median

5.1.1 Manufacturing sector: balancing property and propensity scores

The balancing property is satisfied for manufacturing sector (appendix 3.e). The propensity scores are generated as well. The mean for propensity scores is 0.087 for 65 treated units and 0.055 for 1063 controls. The standard deviations are 0.092 and 0.042 respectively. Expectedly, the average probability of being subsidized is higher for treated than control units. Moreover, The propensity score graphs for treated and non-treated can be illustrated relaxing or considering common support option. Figures (4) and (5) illustrate the propensity score graphs for the former and the latter cases, respectively. The figures can be depicted using other settings for the bin and interval used for propensity score (appendix 3.g).

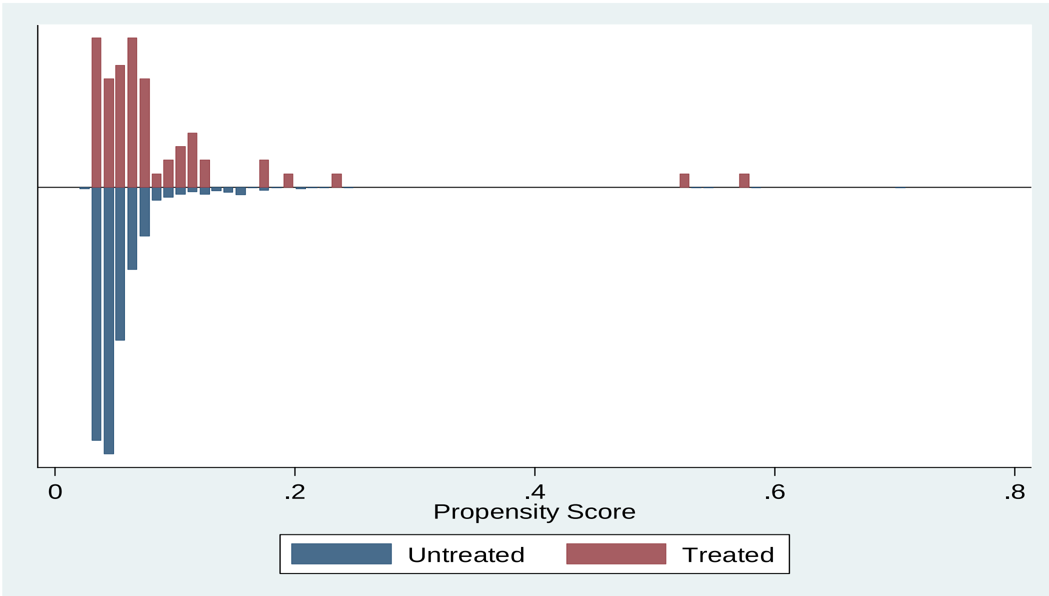

Figure 4. propensity score distribution for treated and untreated in manufacturing sector

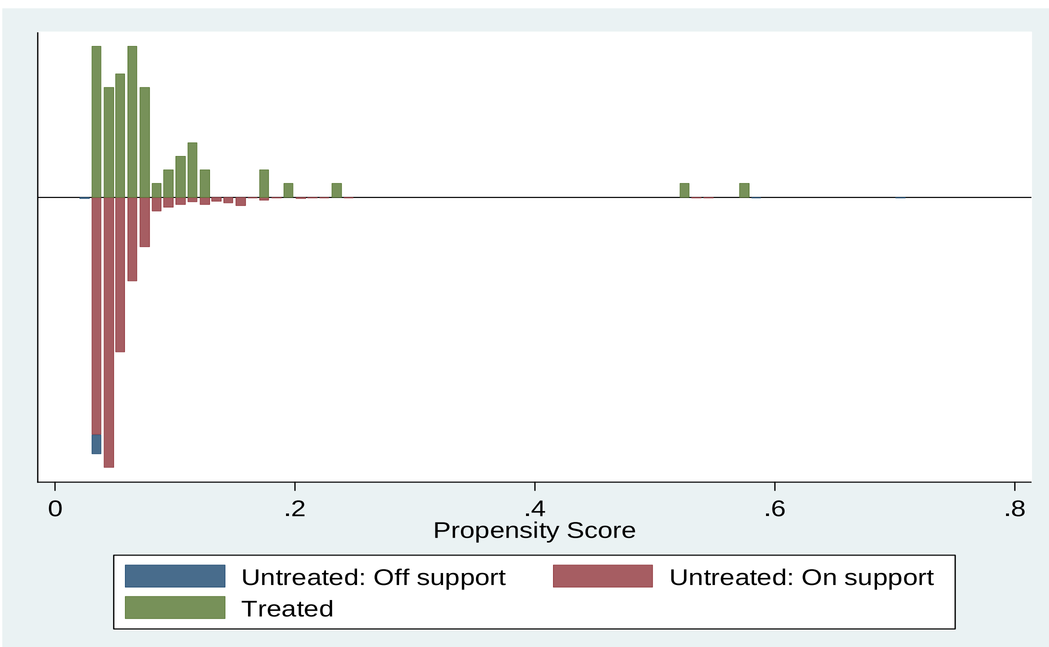

Figure 5. propensity score distribution for treated and untreated in manufacturing sector considering common support option[91]

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[91] psgraph, bin(100) treated(treatment) support(comsup) pscore(myscore_manufacturing)

5.1.2 ICT sector: balancing property and propensity scores

The balancing property is satisfied for ICT sector (appendix 3.f). The propensity scores are generated as well. The mean for propensity scores is 0.147 for 21 treated units and 0.060 for 291 controls. The standard deviations are 0.183 and 0.056 respectively. Expectedly, the average probability of being subsidized is higher for treated than control units. Moreover, The propensity score graphs for treated and non-treated can be illustrated relaxing or considering common support option. Figures (6) and (7) illustrate the propensity score graphs for the former and the latter cases, respectively. The figures can be depicted using other settings for the bin and interval used for propensity score (appendix 3.g).

5.1.3 The effect of R&D subsidies on TFP outcome measures: Manufacturing and ICT sectors

Table (10) shows the ATET and ATE related to the effect of R&D subsidies on targeted outcome variables measured by treatment effect PSM method (default nearest neighbor), nearest neighbor estimator (made by attnd command only for ATET and kernel estimator). Outcome variables consist of total factor productivity change and two decomposed measures of efficiency change and technological (technical frontier) change between two points in time (two consecutive years) measured for manufacturing and ICT sectors. The significant coefficients are shown bold and the number of treated observations versus control observations are reported.

During the process of measuring treatment effects, the subsidized and control units are getting matched based on their propensity scores generated by balancing on observable factors. Therefore, after average treatment effect measures are produced, it is possible to check the summary of balancing propensity scores and balancing graphs on observables. In the following and before discussing the results, some treatment effect balancing summary and graphs are displayed for specific treatment effect on outcomes.[92] For instance, using PSM technique (teffects

[92] There are 3 outcome measures being used by 5 different estimators for 5 consecutive years within two main industries, hence, 150 effect measures are possible. As long as balancing check can be carried out after each treatment effect measurement, we only choose the effect of treatment for some cases with a specific outcome for a specific year-lag using a specific method within a specific industry.

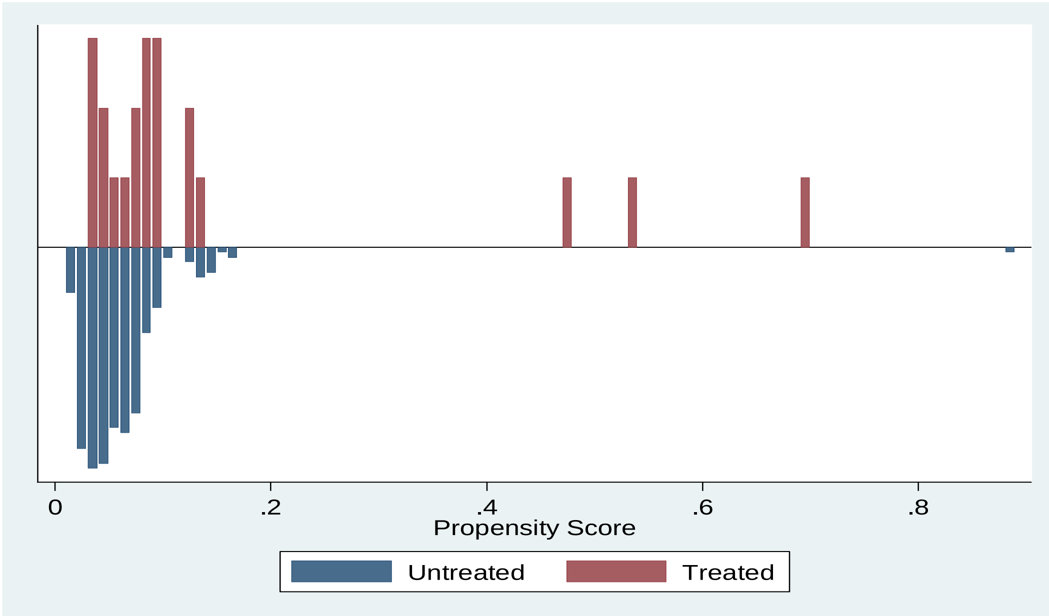

Figure 6. propensity score distribution for treated and untreated in ICT sector[93]

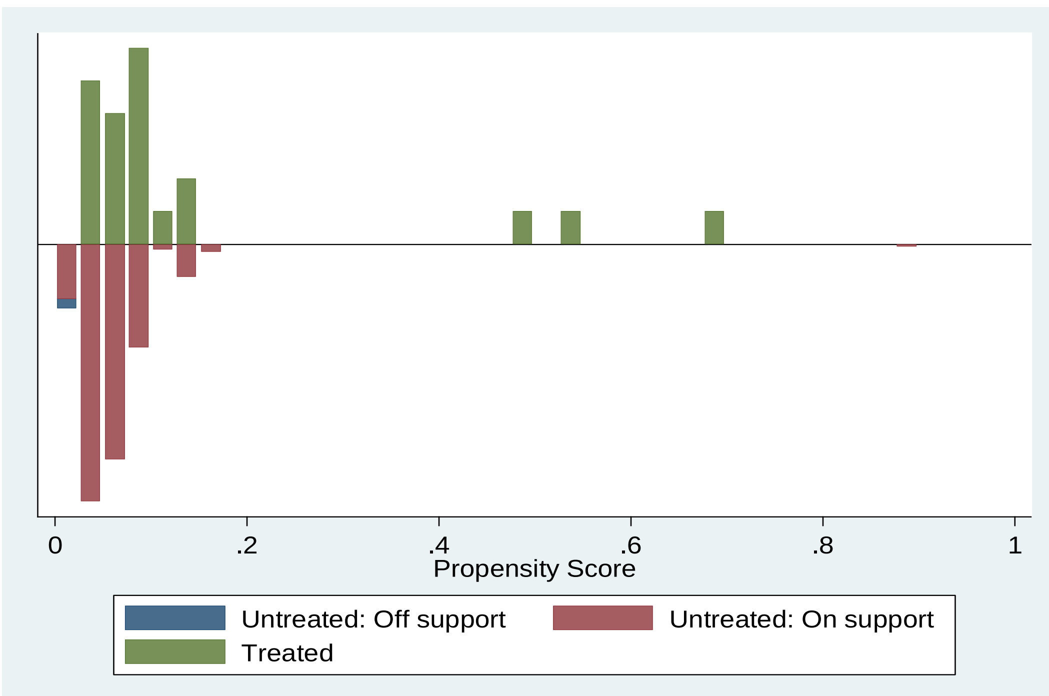

Figure 7. propensity score distribution for treated and untreated in ICT sector considering common support option

[93] psgraph, bin(100) treated(treatment) pscore(pscores2_ICT)

Table 10. Results for Average treatment effect on treated (ATET) and average treatment effect on the population (ATE)

(a) Results for average effect of R&D subsidies on TFP change for subsidized firms (Average treatment effect: ATET): Manufacturing and ICT sectors

Manufacturing

	TFPCH$^{\Delta}$				**EFFCH**$^{\Delta\Delta}$				**TECHCH**$^{\Delta\Delta\Delta}$			
	PSM: ATET†	**NN ATET**†† **(method 1)**	**NN ATET**††† **(method 2)**	**Kernel: ATET**††††	**PSM: ATET**	**NN ATET (method 1)**	**NN ATET (method 2)**	**Kernel: ATET**	**PSM: ATET**	**NN ATET (method 1)**	**NN ATET (method 2)**	**Kernel: ATET**
1-year lag	0.022	-0.032	0.001	-0.009	0.078	0.068	0.040	0.024	-0.048	**-0.103****	-0.027	-0.027
	(0.037)	(0.036)	(0.042)	(0.035)▼	(0.049)	(0.054)	(0.067)	(0.046)	(0.049)	**(0.054)**	(0.039)	(0.043)
Treated/Control^^	65/940	65/940	71/241	71/1245	65/940	65/940	71/241	71/1245	65/940	65/940	71/241	71/1245
2-year lag	**0.051***	0.023	0.025	0.009	0.039	-0.054	0.040	-0.024	0.005	0.083	0.030	0.033
	(0.032)	(0.070)	(0.050)	(0.035)	(0.046)	(0.069)	(0.067)	(0.039)	(0.049)	(0.063)	(0.064)	(0.036)
Treated/Control	59/752	59/752	71/225	71/1245	59/752	59/752	71/225	71/1245	59/753	59/752	71/225	71/1245
3-year lag	-0.009	-0.045	-0.042	-0.008	0.032	0.006	-0.087	-0.014	-0.055	-0.055	0.019	0.000
	(0.038)	(0.074)	(0.042)	(0.033)	(0.053)	(0.074)	(0.053)	(0.041)	(0.055)	(0.076)	(0.045))	(0.041)
Treated/Control	36/564	36/564	71/217	71/1245	36/564	36/564	71/217	71/1245	36/564	36/564	71/217	71/1245
4-year lag	0.018	0.012	0.033	0.010	-0.044	-0.100	0.047	-0.020	0.028	0.080	-0.049	0.014
	(0.043)	(0.037)	(0.044)	(0.034)	(0.068)	(0.065)	(0.043)	(0.042)	(0.059)	(0.061)	(0.041)	(0.030)

Treated/Control	23/376	23/376	71/202	71/1245	23/376	23/376	71/202	71/1245	23/376	23/376	71/202	71/1245
5-year lag	0.028	0.075	0.046	0.052	0.031	**0.088***	-0.022	0.056	-0.018	-0.044	0.042	-0.017
	(0.062)	(0.073)	(0.040)	(0.080)	(0.069)	**(0.047)**	(0.053)	(0.045)	(0.072)	(0.069)	(0.040)	(0.058)
Treated/Control	9/188	9/188	71/191	71/1245	9/188	9/188	71/191	71/1245	9/188	9/188	71/191	71/1245

ICT

	TFPCH$^{\Delta}$				**EFFCH$^{\Delta\Delta}$**				**TECHCH$^{\Delta\Delta\Delta}$**			
	PSM: ATET	**NN ATET (method 1)**	**NN ATET (method 2)**	**Kernel: ATET**	**PSM: ATET**	**NN ATET (method 1)**	**NN ATET (method 2)**	**Kernel: ATET**	**PSM: ATET**	**NN ATET (method 1)**	**NN ATET (method 2)**	**Kernel: ATET**
1-year lag	-0.059	0.038	-0.013	-0.008	-0.064	0.026	0.015	-0.009	0.006	0.016	-0.022	0.008
	(0.079)	(0.054)	(0.085)	(0.044)	(0.097)	(0.059)	(0.088)	(0.053)	(0.035)	(0.026)	(0.046)	(0.026)
Treated/Control	21/260	21/260	23/66	23/341	21/260	21/260	23/66	23/341	21/260	21/260	23/66	23/341
2-year lag	0.120	0.049	0.075	0.031	0.139	0.058	0.073	0.054	-0.018	0.000	0.012	-0.011
	(0.090)	(0.071)	(0.074)	(0.069)	(0.110)	(0.082)	(0.087)	(0.081)	(0.046)	(0.037)	(0.032)	(0.034)
Treated/Control	19/208	19/208	23/66	23/341	19/208	19/208	23/66	23/341	19/208	19/208	23/66	23/341
3-year lag	0.042	0.121	**0.128***	0.059	0.103	0.126	0.136	0.105	-0.034	0.015	0.007	-0.021
	(0.107)	(0.130)	**(0.083)**	(0.129)	(0.131)	(0.164)	(0.107)	(0.143)	(0.046)	(0.057)	(0.035)	(0.042)
Treated/Control	9/156	9/156	23/66	23/341	9/156	9/156	23/66	23/341	9/156	9/156	23/66	23/341
4-year lag	0.176	0.179	0.069	0.107	0.121	0.149	0.112	0.144	0.095	**0.0670***	-0.017	**0.002****

	(0.157)	(0.220)	(0.126)	(0.019)	(0.213)	(0.226)	(0.143)	(0.258)	(0.058)	**(0.037)**	(0.038)	**(0.063)**
Treated/Control	9/156	9/156	23/62	23/341	9/156	9/156	23/62	23/341	9/156	9/156	23/62	23/341
5-year lag	—▼▼	—	$\mathbf{0.470}^{***}$	$\mathbf{0.410}^{*}$	—	—	$\mathbf{0.577}^{***}$	0.544	—	—	-0.030	-0.056
			(0.154)	**(0.292)**			**(0.192)**	(0.471)			(0.039)	(0.062)
Treated/Control	2/104	2/104	23/59	23/341	2/104	2/104	23/59	23/341	2/104	2/104	23/59	23/341

(b) Results for average effect of subsidies on TFP change for all the firms (Average treatment effect: ATE): Manufacturing and ICT sectors

Manufacturing

	$\mathbf{TFPCH}^{\Delta}$		$\mathbf{EFFCH}^{\Delta\Delta}$		$\mathbf{TECHCH}^{\Delta\Delta\Delta}$	
	PSM: ATE†	**NN: ATE**††	**PSM: ATE**	**NN: ATE**	**PSM: ATE**	**NN: ATE**
1-year lag	-0.0266	-0.039	-0.0126	0.008	**-0.011***	-0.047
	(0.032)	(0.051)	(0.048)	(0.059)	**(0.053)**	(0.055)
Treated/Control	65/940	71/241^^	65/940	71/241	65/940	71/241
2-year lag	0.000	-0.039	-0.013	0.008	-0.014	-0.047
	(0.019)	(0.051)	(0.046)	(0.059)	(0.049)	(0.055)
Treated/Control	59/752	71/225	59/752	71/225	59/752	71/225
3-year lag	$\mathbf{-0.050}^{*}$	-0.027	-0.022	-0.006	-0.041	-0.042
	(0.028)	(0.034)	(0.043)	(0.054)	(0.38)	(0.059)
Treated/Control	36/564	71/217	36/564	71/217	36/564	71/217

4-year lag	0.004	0.000	-0.011	-0.037	-0.010	0.009
	(0.038)	(0.034)	(0.48)	(0.041)	(0.024)	(0.029)
Treated/Control	23/376	71/202	23/376	71/202	23/376	71/202
5-year lag	0.107	0.028	**0.132****	**0.087****	**-0.056****	**-0.076****
	(0.076)	(0.042)	**(0.066)**	**(0.041)**	**(0.027)**	**(0.030)**
Treated/Control	9/188	71/191	9/188	71/191	9/188	71/191

ICT

	TFPCH^Δ		**EFFCH^ΔΔ**		**TECHCH^ΔΔΔ**	
	PSM: ATE	**NN: ATE**	**PSM: ATE**	**NN: ATE**	**PSM: ATE**	**NN: ATE**
1-year lag	-0.0491	-0.006	-0.046	-0.016	0.0027	0.018
	(0.074)	(0.055)	(0.68)	(0.057)	(0.013)	(0.020)
Treated/Control	21/260	21/260	21/260	21/260	21/260	21/260
2-year lag	0.104	0.109	0.116	0.108	-0.005	0.004
	(0.087)	(0.120)	(0.096)	(0.159)	(0.35)	(0.031)
Treated/Control	19/208	19/208	19/208	19/208	19/208	19/208
3-year lag	0.068	0.142	0.162	0.225	**-0.085****	-0.075
	(0.10)	(0.203)	(0.15)	(0.276)	**(0.36)**	(0.058)

Treated/Control	9/156	9/156	9/156	9/156	9/156	9/156
4-year lag	0.157	0.346	0.219	0.477	-0.024	-0.063
	(0.46)	(0.254)	(0.63)	(0.355)	(0.092)	(0.068)
Treated/Control	5/104	5/104	5/104	5/104	5/104	5/104
5-year lag	—	—	—	—	—	—
Treated/Control						

Δ TFPCH: TFP Change

ΔΔ EFFCH: Efficiency Change

ΔΔΔ TECHCH: Technological Change

* %90 level of confidence

** %95 level of confidence

*** %99 level of confidence

† [Command: teffects psmatch (outcome observables) (treatment)], The default setting is nearest neighbor (NN) estimator.

†† NN Method 1: [Command: teffects nnmatch (outcome observables) (treatment)].

††† NN Method 2: ATET NN with attnd command: Nearest neighbor matching estimator (random draw version).

†††† Kernel estimator (Epanechnikov): Default bandwidth(0.6). Standard errors are generated using bootstrap.

†, ††&††† All methods apply the same nearest neighbor estimators but with different algorithms in STATA.

▼ Analytical standard errors cannot be computed. Bootstrapped standard errors are generated.

^^ The number of treated and controls in (NN (att) and kernel (attk)) refer to the actual number of nearest neighbor and kernel matches regardless of the missing values generated. This is the reason why we observe different number of treated and controls with respect to the other command of PSM treatment effect (teffect). For instance, the actual number is 71, while there are 6 missing values generated after running the command, hence, making the treated the same 65 observations. The same holds for all the different numbers. The standard errors in NN (att command) are the analytical, while for Kernel the standard errors are corrected by bootstrap.

▼▼ Not sufficient number of nearest-neighbor matches for observation. Therefore, the analysis cannot be carried out.

psmatch), the effect of R&D subsidies on TFP change (tfpch_lagged3) in manufacturing sector and after 3 years (3-year lag) is measured significantly negative (-0.050). The balancing process on observables (size and age) for treated and controls can be shown after treatment effect analysis as well after each effect measurement. In the following figures (Fig. (8)_Fig (11)), some examples of balancing based on basic covariates have been illustrated.[94] Some other balancing illustrations beside summarization of the effect measurement mainly for significant effects are displayed in appendix (3.h). The results will be explained in the section related to discussion.

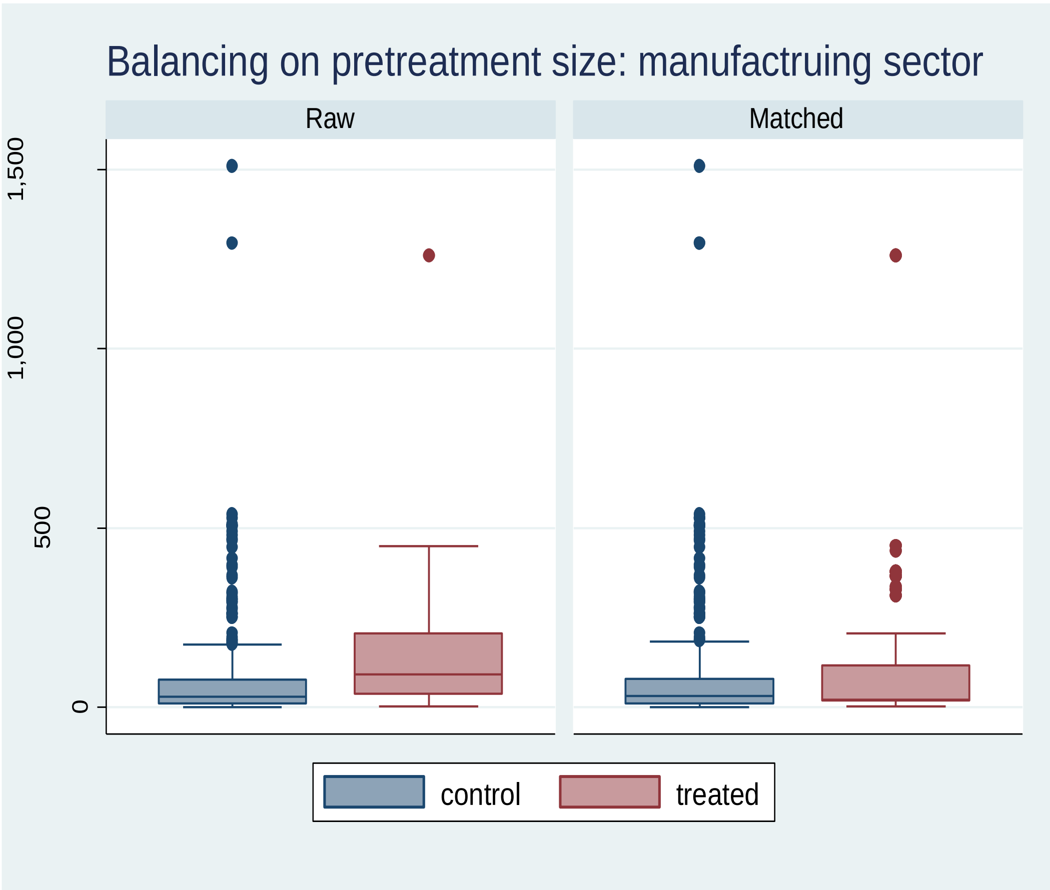

Figure 8. Balancing box-plot graphs for size variable after treatment effect measurement

[94] Command: tebalance [box or density]

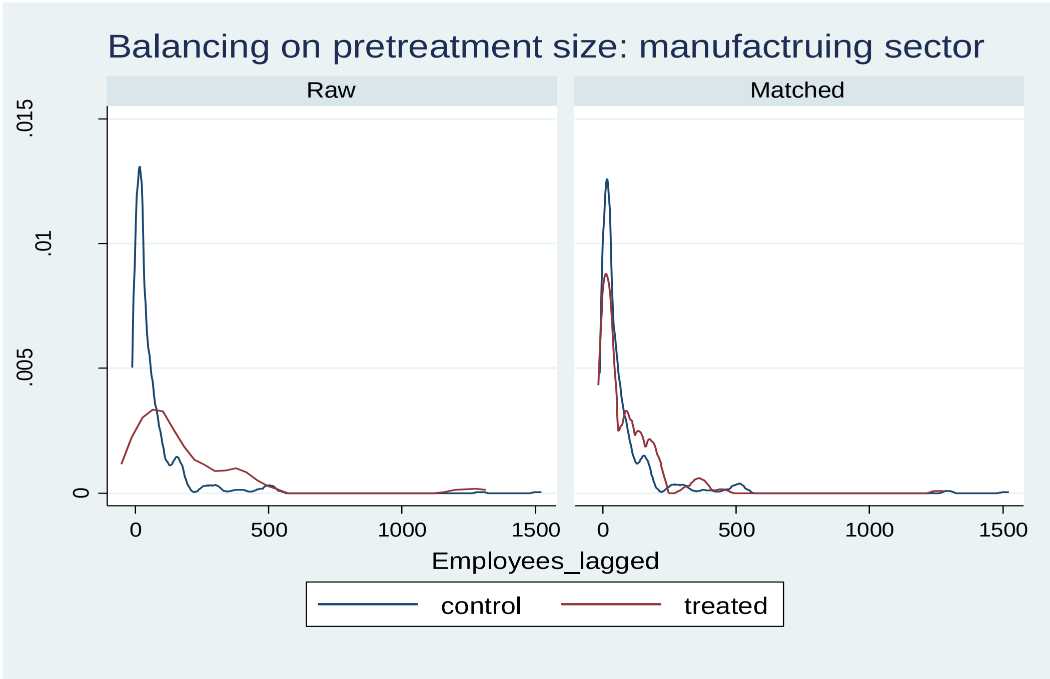

Figure 9. Balancing kernel density graphs for size variable after treatment effect measurement

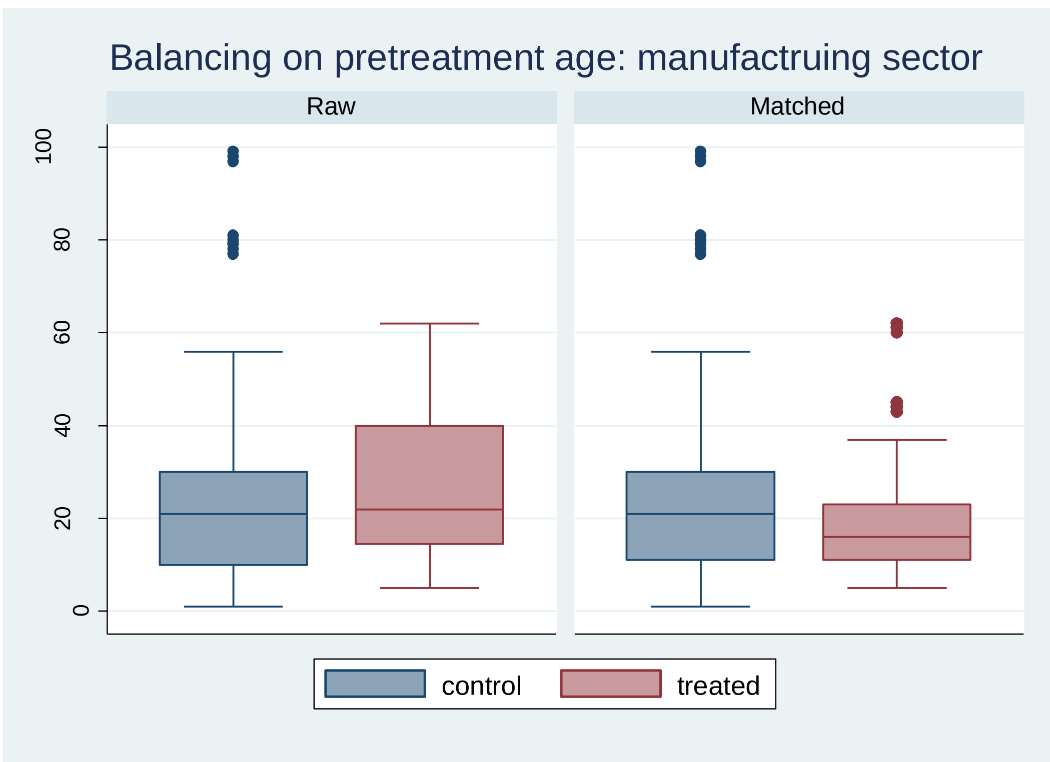

Figure 10. Balancing box-plot graphs for age variable after treatment effect measurement

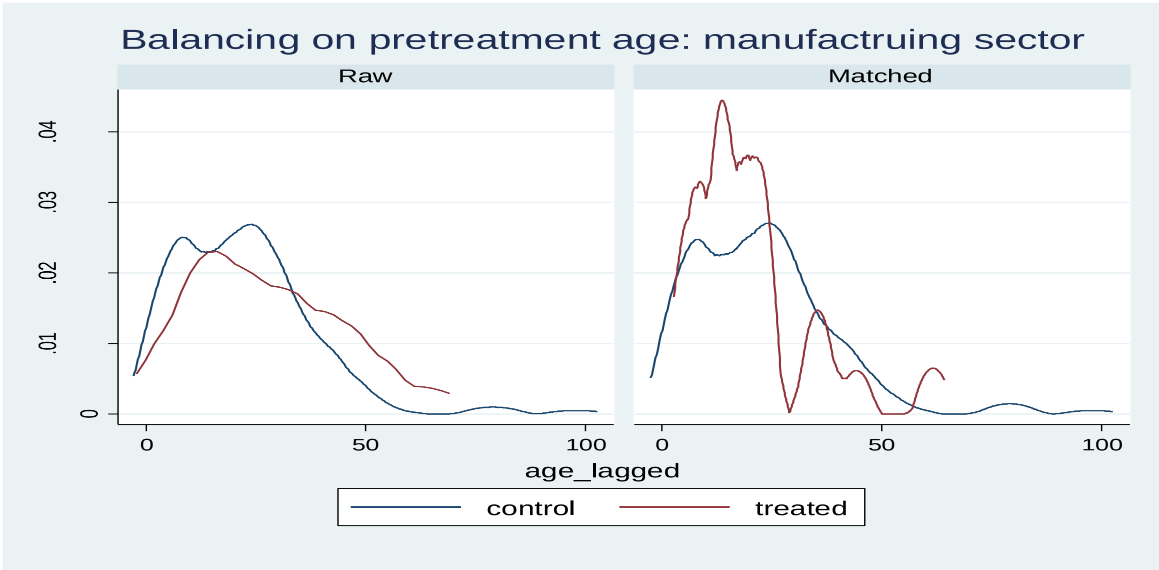

Figure 11. Balancing kernel density graphs for age variable after treatment effect measurement

5.1.4 R&D subsidies effect on TFP measures : Low-medium and high-tech industries

In previous section we have focused on two main industries in which R&D subsidies possess the highest frequencies significantly different with other sectors. The treatments are not sufficiently high in other sectors to measure the effect individually for them. At the same time as shown in appendix(3.i), the balancing property for two other sectors is not satisfied.

On the other hand, as stated in the literature review and consequently research hypotheses sections, industry dynamics may certainly influence the channels which lead the effect of the subsidies on outcome measures. Almost all evaluation studies have considered the effect of industries on the impact of subsidies on targeted variables, either by taking into account the industry factor as a control variable (Wallsten, 1999; Busom, 1999; Lerner, 1999; Lach, 2002; González, Jaumandreu, & Pazo, 2005; Clausen, 2009; Czarnitzki et al., 2011; Bronzini & Iachini, 2014; Bronzini & Piselli, 2016) or by direct execution of the impact evaluation for particular industries (Klette, Møen & Griliches, 2000; Heshmati & Lööf, 2005; Atzeni & Carboni, 2008; De Jorge and Suàrez, 2011; Acosta et al., 2015; Criscuolo et al., 2016; Marino et al., 2016). Moreover, Sissoko (2011) suggests to categorize firms based on the distance to technology frontier. He believes firms far from the frontier are more likely to benefit from R&D support. Finally, Bernini et al. (2017) believes the classification of firms into the industries they are operating must become a standard in treatment effect evaluation studies.

Concentrating on the technological intensity of industries which subsidies allocations happen in our context (table 9) and based on the literature and studies reviewed in chapter two, the sectors are divided into two main categories; a) Low-medium technological industries including manufacturing, construction and wholesale retail sectors; and b) High-tech industries including ICT and scientific and technical activity sectors. The empirical advantage of this classification is the retrieval of other treatments being missed due to evaluation the effect only for two main industries. In other words, The treatment and control frequencies for each of these classifications is the sum of their counterparts in each sector. Consequently, the matches are searched not separately inside each class but within all related industries. The following section measures the effect of R&D subsidies on TFP measures considering these two types of industries.

5.1.4.a Low-medium tech industries

The total treatments frequency is 79, the sum of subsidies allocations in manufacturing, construction and wholesale retail sectors (table 9). The total number of controls equals 3365 units. The same as matching procedures used previously for the evaluation, the first step is checking the balancing property. Balancing property is satisfied and the propensity distribution for subsidized and controls are as the following figure (12).

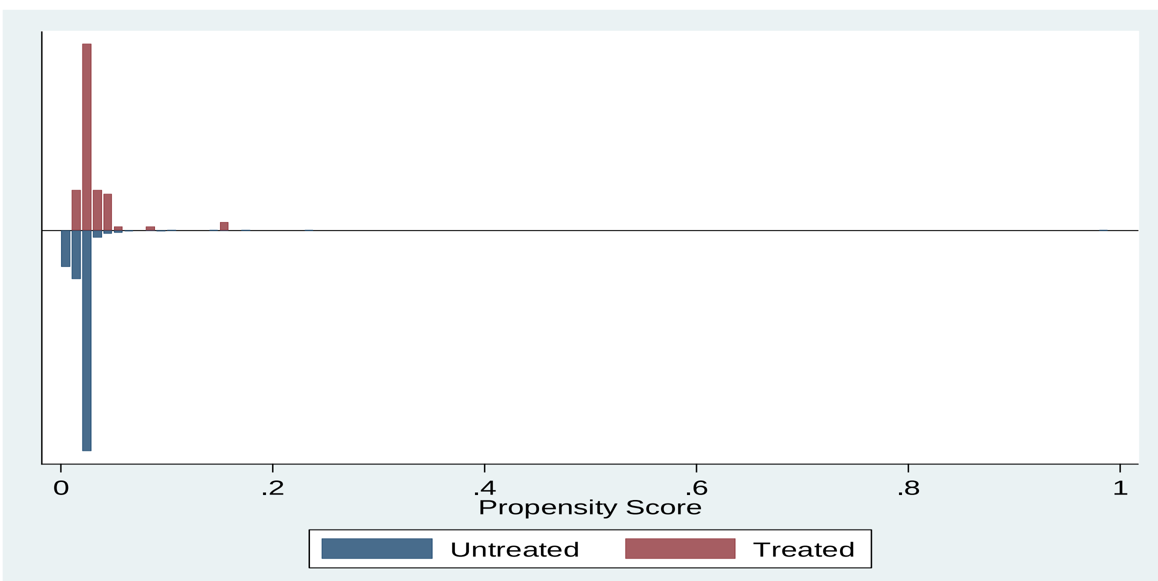

Figure 12. Propensity scores distribution for treated and untreated

The measurement of R&D subsidies effect on the outcome variables shows that there are no average treatment effect on treated (ATET) at any level of analysis. However, for average treatment effect on the population (ATE), the following effects shown in bold in table (11) are significant. The balancing for matching on observables can be checked after treatment effect is measured in the following figures (13) and (14). The results will be explained in the section related to discussion. Moreover, some examples of how the effect is measured for different outcome variables is displayed in appendix (3.j).

5.1.4.b High tech industries

The total treatments frequency is 32, the sum of subsidies allocations in ICT and technical activity sectors (table 9). The total number of controls equals 675 units. The propensity distribution for subsidized and controls are as the following figure (15). The measurement of R&D subsidies effect on the outcome variables for the population and treated firms are reported in Table 12 (only significant effects). The balancing for matching on observables can be checked after treatment effect is measured in the following figures (16) and (17). Moreover, some examples of how the effect is measured for different outcome variables is displayed in appendix (3.j).

At this point the R&D subsidies effect analysis have been carried out for subsidized and control units for each industry. The measurement results relate to two main industries (in case of grants allocation intensity) and two groups of industries; low-medium and high tech industries in which R&D subsidies occur. The analysis can be also implemented for all the sample firms in all sectors pooled together. This can be done by controlling for industry as another observable factor or assuming all firms within all industries can be matched and compared. However, investigation of balancing property satisfaction shows that the balancing assumption is not satisfied when all firms are pooled together (Appendix 3.k)

Table 11. ATE estimations using PSM for low-medium tech industries

	ATE for low-medium Tech industries					
	TFPCH$^{\Delta}$	Treated vs. Controls.	EFFCH$^{\Delta\Delta}$	Treated vs. Controls.	TECHCH$^{\Delta\Delta\Delta}$	Treated vs. Controls.
1-year lag	-0.115	72/2338	-0.071	72/2388	-0.038	72/2338
	(0.073)		(0.092)		(0.062)	
2-year lag	**-0.152****	65/1903	**-0.182****	65/1903	0.063	65/1903
	(0.74)		**(0.87)**		(0.063)	
3-year lag	**-0.173***	39/1437	**-0.175***	39/1437	0.018	39/1437
	(0.94)		**(0.10)**		(0.071)	
4-year lag	-0.032	23/961	0.053	23/961	**-0.085*****	23/961
	(0.055)		(0.071)		**(0.030)**	
5-year lag	-0.085	9/483	**-0.082***	9/483	0.003	9/483
	(0.063)		**(0.049)**		(0.047)	

Δ TFPCH: TFP Change ΔΔ EFFCH: Efficiency Change ΔΔΔ TECHCH: Technological Change

* %90 level of confidence ** %95 level of confidence *** %99 level of confidence

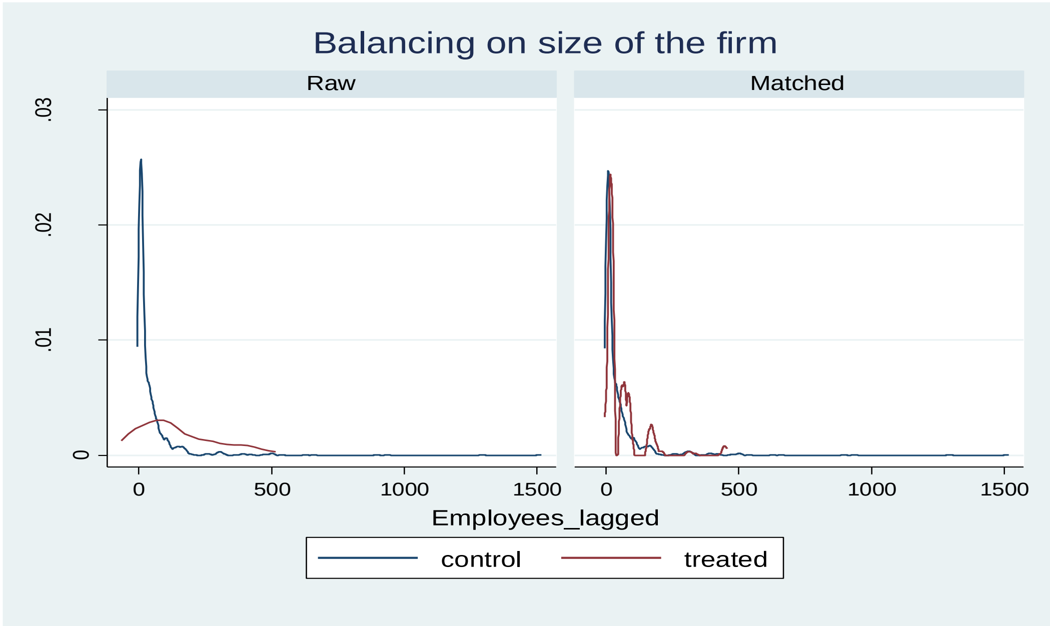

Figure 13. Balancing on size using propensity scores (kernel density)

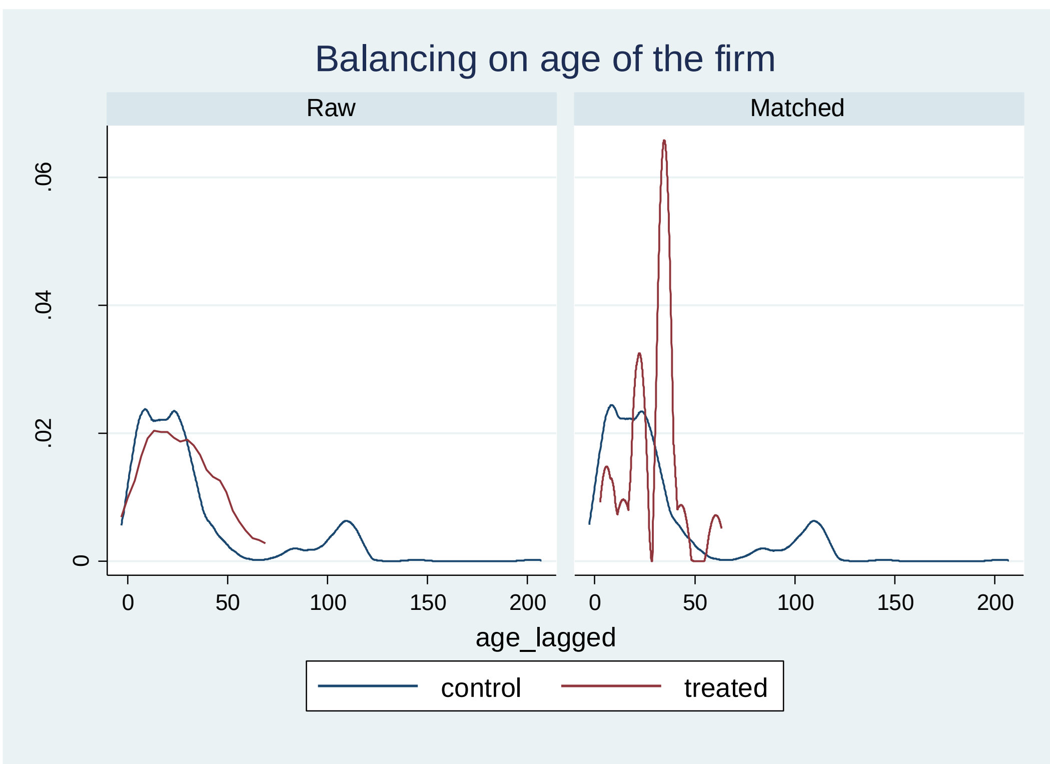

Figure 14. Balancing on age using propensity scores (kernel density)

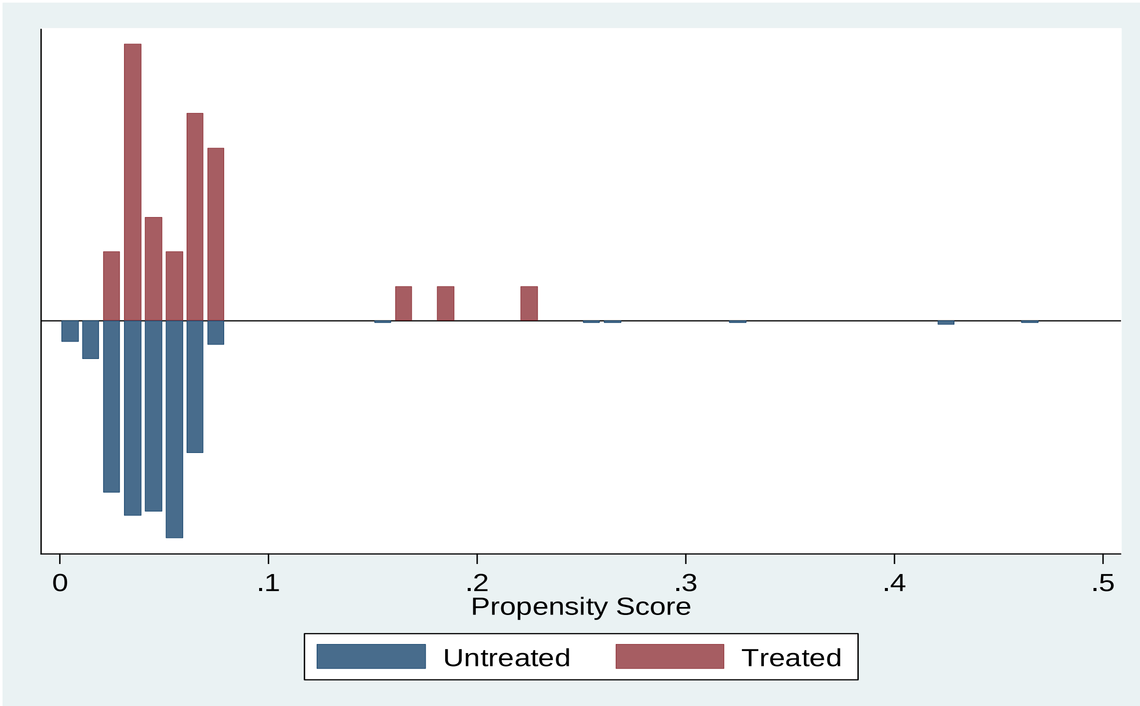

Figure 15. Propensity scores distribution for treated and untreated

Table 12. ATTE and ATE estimations using PSM for high tech industries

ATT/ATE for High Tech industries

	TFPCH	Treated vs. Controls	EFFCH	Treated vs. Controls	TECHCH	Treated vs. Controls
1-year lag						
2-year lag	**ATET: 0.127***	**26/378**				
	(0.69)					
3-year lag					**ATE:-0.061****	**13/290**
					(0.026)	
4-year lag					**ATE: -0.111**	**7/195**
					(0.064)	
5-year lag						

Δ TFPCH: TFP Change ΔΔ EFFCH: Efficiency Change ΔΔΔ TECHCH: Technological Change

* %90 level of confidence ** %95 level of confidence *** %99 level of confidence

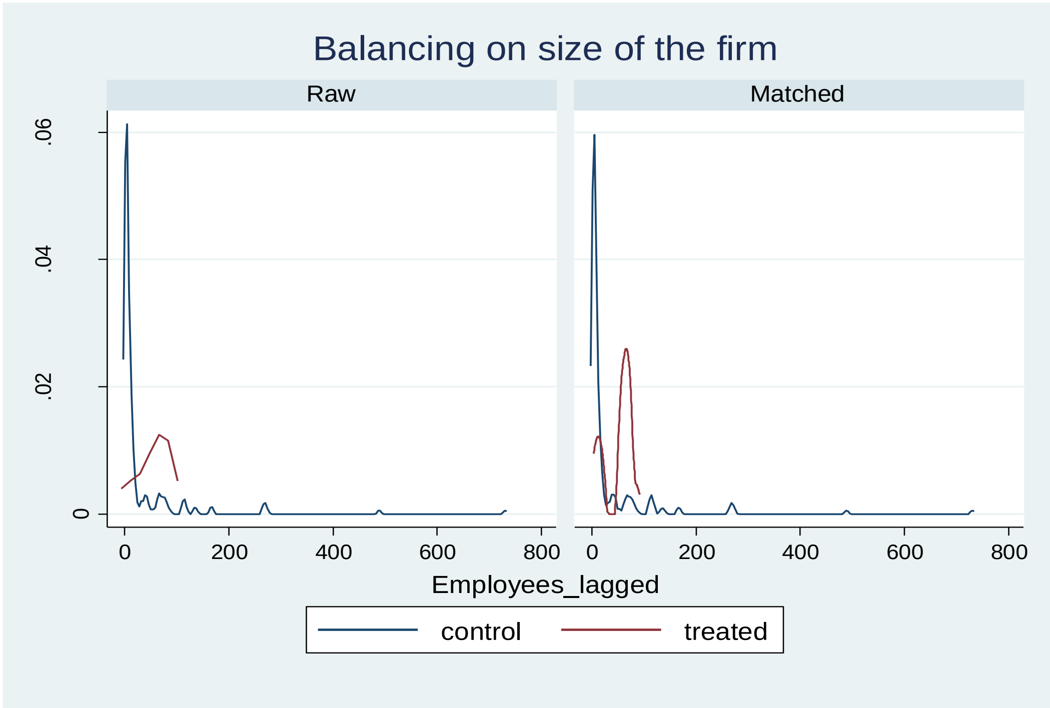

Figure 16. Balancing on size using propensity scores (kernel density)

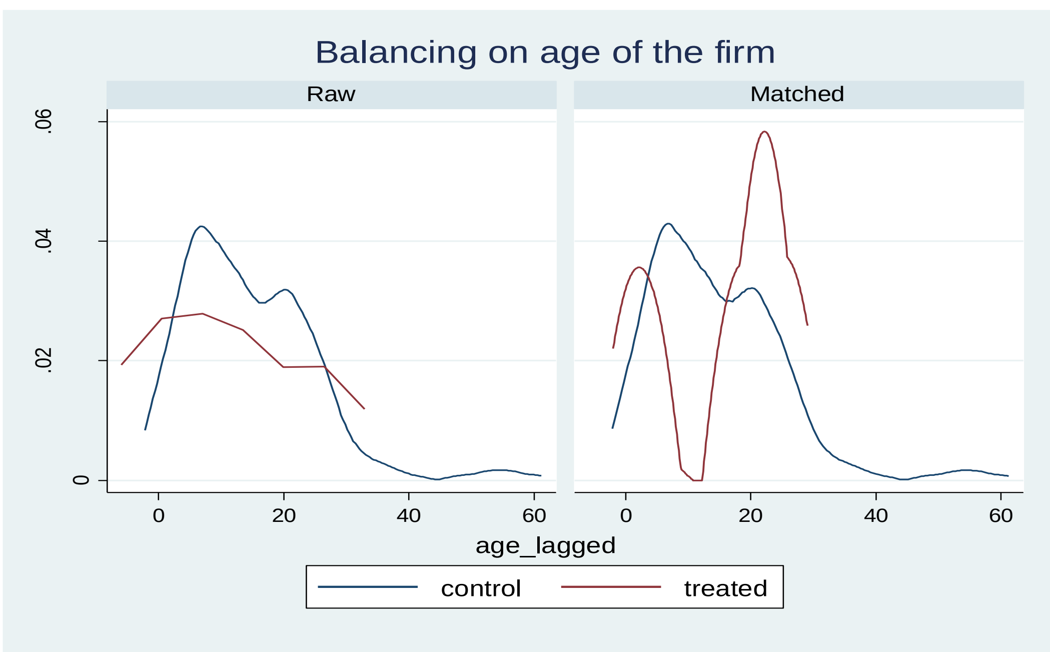

Figure17. Balancing on age using propensity scores (kernel density)

5.1.5 effect of R&D subsidies on TFP measures based on selection procedure

Another important factor which can influence the effect of R&D subsidies on targeted outcome is selection process. As explained in table (1), the selection procedure is mainly divided into three categories of automatic, evaluative and negotiable mechanisms. However, because the two former methods almost resemble each other in selection criteria, we classify the selection procedures into two main procedures of automatic and evaluative. Therefore we run PSM ATE and ATET measurements for all pooled firms. Out of 111 treatments, 53 are automatic and 58 are evaluative. These treatments are dispersed through different industries. Therefore, as long as most of the subsidies happen in manufacturing industry and to keep the homogenous sector condition for matching we compare the effect of different evaluation method within manufacturing sector. In the sector 40 subsidies are allocated through evaluative method and 31 through automatic procedure (in total 71 treated observations). Balancing property holds for both types of evaluation methods. Table(13) in the following shows the results for estimations based on selection procedures.

Furthermore, we have additionally analyzed the average R&D subsidies effect based on the first industry digit of ateco 2007 firm activity coding system (table (3.l.1) in appendix (3.l)). The results and a brief discussion is provided in appendix. However, as long as the first digit classification may include different industries into one industry category, this beside violation of homogenous operating process assumption for DMUs in order to measure relative (in)efficiency and frontier measures, may provide not a proper control group due to estimating propensity scores.

Next sections discuss and conclude the different results related to PSM estimation of R&D subsidies effect on TFP measures, produced in previous sections. The discussion points out to the research hypotheses and deals with the explanations and answers for the related hypotheses arisen in the previous chapter.

Table 13. The effect of Automatic and Evaluative selection procedures on TFP measures

Manufacturing Industry		TFPCH Automatic Selection	TFPCH Evaluative Selection	EFFCH Automatic Selection	EFFCH Evaluative Selection	TECHCH Automatic Selection	TECHCH Evaluative Selection
1-year lag	PSM:ATE	0.047	-0.035	0.105	-0.009	-0.052	-0.023
		(0.035)	(0.084)	(0.086)	(0.096)	(0.078)	(0.085)
		(29/911)	(36/904)	(29/911)	(36/904)	(29/911)	(36/904)
	PSM:ATET	-0.021	-0.034	-0.032	-0.021	0.000	0.000
		(0.054)	(0.067)	(0.076)	(0.067)	(0.067)	(0.067)
		(29/911)	(36/904)	(29/911)	(36/904)	(29/911)	(36/904)
2-year lag	PSM:ATE	0.104	-0.027	0.086	-0.090	-0.004	0.074
		(0.065)	0.020	(0.073)	0.069	(0.080)	(0.074)
		(27/725)	(32/720)	(27/725)	(32/720)	(27/725)	(27/725)
	PSM:ATET	-0.023	-0.005	0.010	0.007	-0.016	-0.016
		(0.061)	(0.069)	(0.083)	(0.061)	(0.072)	(0.053)
		(27/725)	(32/720)	(27/725)	(32/720)	(27/725)	(32/720)
3-year lag	PSM:ATE	**-0.068****	0.036	-0.047	0.041	-0.007	-0.048
		0.030	(0.086)	(0.080)	0.048	(0.078)	(0.042)
		(19/545)	(17/547)	(19/545)	(17/547)	(19/545)	(17/547)
	PSM:ATET	**-0.065****	0.094	-0.075	**0.147****	0.031	-0.077
		(0.034)	(0.082)	(0.087)	**(0.078)**	(0.086)	(0.092)
		(19/545)	(17/547)	(19/545)	**(17/547)**	(19/545)	(17/547)
4-year lag	PSM:ATE	-0.027	0.069	-0.001	0.054	**-0.110***	-0.012
		(0.037)	(0.081)	(0.070)	(0.073)	**0.0589**	0.029
		(12/364)	(11/365)	(12/364)	(11/365)	(12/364)	(11/365)
	PSM:ATET	-0.026	0.061	-0.058	-0.007	0.021	0.033
		(0.035)	(0.061)	(0.111)	(0.101)	(0.094)	(0.091)
		(12/364)	(11/365)	(12/364)	(11/365)	(12/364)	(11/365)
5-year lag	PSM:ATE	-0.007	0.036	0.061	0.027	-0.044	-0.020
		(0.034)	(0.114)	(0.042)	(0.066)	(0.059)	(0.035)
		(6/182)	(3/185)	(6/182)	(3/185)	(6/182)	(3/185)
	PSM:ATET	-0.021	0.199	-0.031	**0.0246*****	-0.004	**-0.134*****
		(0.023)	(0.185)	(0.114)	**(0.058)**	(0.125)	**(0.034)**
		(6/182)	(3/185)	(6/182)	**(3/185)**	(6/182)	**(3/185)**

6. Discussion and policy implications

Globally, the results show mixed and heterogenous effects of subsidies on TFP measures. As discussed in chapter one, many other studies reach to the same idea that the effect measured on TFP measures are mixed (David, Hall & Toole, 2000; Pellegrini et al., 2011; Caloffi et al., 2016; Dimos and Pugh, 2016). However, by concentrating on the main trends of the effect of public R&D support on TFP change, efficiency change and technological frontier change, we can characterize the effects of the place-based policy on TFP measures as the following table (14). The main findings about the direction of the policy effects on TFP measures reconfirms the part of the literature declaring the mixed and heterogenous results for the effect of R&D subsidies on outcome targeted variables.

Average treatment effect (ATE) on the whole population if significant is mainly negative except for the positive effect of policy on efficiency change in long run for manufacturing sector (13.2% and 8.7%). The ATE long-run effect of subsidies on technological change is negative for both manufacturing (-5.6 or -7.6% after five years) and ICT (-8.5% after three years), low-medium tech (-8.5% after four years) and high tech sectors (-6.1% after three years and -11.1% after four years). This shows the policy has not satisfied the long run effect on technological progress for the whole population. This is more significant when the selection procedure to support R&D projects are automatic and without pre-evaluation of the project. However, the R&D program positively affect the relative efficiency of firms in manufacturing sector in the long run.[95] All in all, total factor productivity decreases through time for manufacturing (-5%) and low-medium tech sectors (-17.3%), while it does not show to have any effect for ICT and high tech sectors.

On the other hand, The effect of R&D subsidies on subsidized firms (ATET) shows a different pattern in comparison with the effect on whole subsidized and non-subsidized firms (ATE). The general trend is that subsidies have no effect on TFP measures. Nevertheless, a positive short term effect shows up for TFP change (5.1% increase after two years).

[95] This effect is realized after five year where the treated and control observations shrink due to lag of the outcome variables.

Table 14. The effect of R&D subsidies on outcome TFP measures

	ATE						ATET					
	Short-term†			Long-run††			Short-term			Long-run		
	TFPCH	EFFCH	TECHCH	TFPCH	EFFCH	TECHCH	TFPCH	EFFCH	TECHCH	TFPCH	EFFCH	TECHCH
Manufacturing	#*	#	-	-	+	-	+	#	-	#	+	#
ICT	#	#	#	#	#	-	#	#	#	++**	+	++
Low-medium Tech	-	-	#	-	--	-	#	#	#	#	#	#
High Tech	#	#	#	#	#	--	+	#	#	#	#	#
Automatic-selection All Obs.	#	#	#	-	#	-	#	#	#	-	#	#
Evaluative selection All Obs.	#	#	#	#	#	#	#	#	#	#	+	-[96]

†One/two years   †† three to five years

* #: No effect   ** In case of being positive/negative for two consecutive years or by two different methods we put more than one +/- sig

[96] This effect (-13.4%) is significant after five years where the number of treated observations is reduced to only three units, making the estimation precision quite low. For effects measured in such a restriction we only report the result and do not make our analysis based on them.

However, this effect is significant for manufacturing and high-tech sectors (12.7% after two years) which represents some mixed and contradictory directions of the effect. The results show positive effect on efficiency change in long run for both manufacturing (8%) and ICT (5.7%) sectors.[97] However, this positive effect regards to the projects being subsidies by evaluative procedure (particularly for manufacturing sector). Moreover, the main finding on ATET measures, show the subsidies have negatively impacted technological progress for manufacturing in short-term (-10.3%) in contrary to the weaker positive effect for ICT industry in long run (6.7%). The results show significant positive effect on all TFP measures in ICT industry in long run.[98]

Sector or industry in which the firm operates is an important factor affecting evaluation and selection process, as law LP 6/99 provokes the province to invest more in IT-related industries based on the ICT development horizon emphasized in European Union strategy design and the regional priorities. Focusing on ICT industry in long run, the subsidies affect positively on efficiency and technological frontier change, leading to a positive effect on total factor productivity change. However, these positive measures except for TFP change do not hold using other evaluation methods (table 10), making it difficult to generalize the effect analysis. This is the case for almost all other estimations.

In evaluative procedure, the effects on efficiency change and technological change are opposite, while the final effect for total factor productivity is insignificant. One interpretation can be that the opposite effects of subsidies on decomposing elements of TFP change, i.e. positive effect for efficiency change and negative effect for technological change, cancel out the ultimate effect for TFP change.

Generally speaking and referred to our research hypotheses, we can imply that the R&D place-based program affect negatively on technological frontier progress (growth) of all firms and positively on efficiency change of subsidized firms (in ICT sector) in the long run. One other impression of the results show that the effect of the R&D subsidies in case of being significant, is more tended to be negative for the whole population of the firms and positive for only subsidized.

[97] The effect shows up after five years which the number of treated are low making us to deal doubtfully with the results. However, using kernel method can reduce the suspicion

[98] 12.8% on TFP change after three years and 4.7% after five years; 5.7% on efficiency change after 5 years and 6.7% on technological change after four years.

This can imply that other non-subsidized firms might have not benefited as subsidized firms from subsidies.

On the other hand, for the whole firms regardless of being treated or not, the program affect positively on efficiency change in the long run (manufacturing sector). R&D subsidies affect negatively on technological progress in long run for the population of whole firms in all sectors. The negative effect of R&D program on technological frontier change shows that innovation incentives have not directed technology leading firms in the region towards moving up the technical frontier in long run[99]. However, it seems the laggard firms behind the technological frontier have increased their relative efficiency absorbing the effect and outcome of R&D subsidies in the related sector particularly manufacturing industry in the long run.

Antonelli and Crespi (2013) in their research notify that the positive relationship between R&D and productivity is much stronger in high-tech firms than in low-tech firms. However, in our analysis the subsidies except showing a positive effect on efficiency change for long run in ICT industry, represent negative effect on technological change. At the same time, R&D subsidies affect negatively on TFP change in manufacturing and low-medium tech industry. Mendonca (2009) explains that high-tech firms are awarded subsidies on merit while low-tech firms most often were given subsidies based on reputation and "name recognition", even in case of misallocation of the funds. This negative effect mainly holds for the grants allocated automatically to R&D projects rather than allocation based on pre-evaluation or negotiation for selection. This, beside the positive effect of evaluative procedure-allocated subsidies effect on TFP change for subsidized firms in long run (ATET), can imply that projects being evaluated for the assignment of subsidies may avoid better the negative effect of the program on TFP change.

Moreover, there can be differences between short term effects (expectedly negative) and long term effects which can be explained by the time to learn, time to stay in a larger market, time to adjust factors proportion and the sluggishness embedded in the impacts of technological improvement (Bernini et al, 2017). This is in line with the effect captured for TFP change especially in case of average treatment effect for the whole population of the firms. However, the effect of support on technological progress change is in contradictory.

[99] Except for a slight effect for subsidized firms in ICT sector.

Finally, sections 1.2, 2 and 3 of Chapter 2 discuss in detail the possible channels and mechanisms leading to different positive/negative effects of R&D subsidies on productivity change measures. However, the casual investigation of this chapter can be completed by a micro effect approach towards the R&D subsidies impact. This will be partially addressed in the next chapter but measuring the effect of R&D policy on a different outcome. Moreover, as long as capturing the dynamics of technological frontier has been beyond the scope of this study, future research can provide a deep analysis of the origins of these causal effects.

7. Conclusion

The chapter has empirically evaluated the effect of R&D subsidies on TFP growth and the elements of TFP growth, i.e. technical (in)efficiency and technological (in)efficiency changes as the determinants of supported firms' growth for a relevant period of time. This evaluation is carried out for the main sectors in which R&D subsidies occur including manufacturing and ICT sectors. The measurement has been implemented for two groups of low-medium tech and high-tech sectors as well. The short-term and long-run effects of R&D subsidies, beside the different treatment effects for two types of selection procedures have also been measured.

TFP is measured using Malmquist Data Envelopment Analysis (DEA) method. Malmquist TFP Index and the decomposed elements of efficiency and technical frontier change are measured using CRS output-orientated DEA-based Malmquist Index methodology applying DMUs' information on three inputs and one output from a balanced dataset. These indices are target variables to measure the impact of place-based R&D subsidization policy. Non-parametric propensity score matching is used to evaluate the impact of policy on total factor productivity change, efficiency change and technical frontier change. The data on policy treatment binary variable and control independent variables (including size and age) are provided in the same balanced panel dataset. The dataset is the outcome of cleaning and merging provincial datasets on R&D subsidies (APIAE) and AIDA financial statement dataset for firms in province of Trento.

Although the study empirically deals with a place-based R&D support program, however, the main goals of this chapter is investigation of the theoretical hypotheses using the contextual settings and data related to a place-based policy. Therefore, the detailed objectives of public R&D policy may not significantly influence the empirical investigation of the causal effect of R&D subsidies on TFP measures. Notwithstanding the theoretical investigation, the by-product of this investigation is the evaluation of the local R&D program leading to place-based policy implications. In any case, The law LP6/99 objectives include stimulating additional private R&D and stabilizing the employment rate which leads to a higher productivity and competitiveness of the firms active in the region. Therefore, even in a practical perspective taking TFP measures as the target outcome variable makes sense.

The impact of R&D subsidies on technical and technological changes can be measured using a quasi-experimental method. The subsidies allocation mechanism, based on provincial law LP 6/99 related to the assignment of direct subsidies to applied research projects in Trento province in Italy, allows us to form a counterfactual setting in which there are treated and non-treated observations within a time span. We have used matching techniques to measure the impact of the public R&D grants on productivity.

Propensity score matching (PSM) is a non-parametric estimator capable of controlling the selection and self-selection biases which occur in evaluation studies. The method measures the average treatment effect on the whole population (ATE) and the average treatment effect on treated (ATET) by comparing the average of the target variables for treated (subsidized) and non-treated units. Based on the law documentations, all the firms operating in the province of Trento are eligible to apply for the subsidies by submission of a project to the province. Hence, assuming zero R&D fixed cost, we can take non-subsidized firms potentially doing R&D and operating in Trento as the controls. The propensity scores are generated due to the balancing of pre-treatment variables (age and size in our setting). In order to check the robustness of the estimations, we measure the effect of R&D subsidies on all TFP measures for the whole population and treated units (in different sectors, different selection procedures and for short-term and long-run time intervals) using PSM nearest neighbor estimator (with two different estimation process) and PSM kernel estimator.

The results show mixed findings about the effect of policy on productivity measures both in terms of the outcome variables and effect time. If the placed-based R&D policy significantly affect the measures, then in most cases this impact is positive on efficiency change and negative on technical frontier change. However, this is not a fit-to-all results through different classifications of the firms, time spans and selection procedure.

The main findings about the direction of the policy effects on TFP measures reconfirms the part of the literature declaring the mixed and heterogenous results for the effect of R&D subsidies on outcome targeted variables. However, it can be implied that the R&D place-based program affect negatively on technological frontier progress (growth) of subsidized firms and positively on efficiency change of subsidized firms (in ICT sector) in the long run. The R&D subsidies have no effect on growth (in terms of TFP change) in steady state, while they show some positive impact in transient state. On the other hand, for the whole firms regardless of being treated or not, the program affect positively on efficiency change in the long run (manufacturing sector). R&D subsidies affect negatively on technological progress in long run for all sectors.

R&D subsidies affect negatively on TFP change in manufacturing and low-medium tech industry. This negative effect mainly holds for the grants allocated automatically to R&D projects rather than allocation based on pre-evaluation or negotiation for selection. As a policy implication, allocation of subsidies based on evaluation method may cause less negative effects on technological frontier change.

A drawback of this study is caused by the limitation related to the relatively low number of R&D subsidies allocations. The place-based policy is restricted to a specific provincial context in which the total number of allocations reaches maximum to 600 grant allocations by a time interval between 2001 to 2013. Furthermore, the data availability due to calculation of TFP measures is restricted for the time interval between 2007 to 2014. This means we can only use the common overlap of datasets between 2007 through 2014. Moreover, as long as one of the input indices applied for TFP measurement is moving average, hence year 2007 is only used to generate this input's measures for 2008. Consequently, applying Malmquist TFP method would generate TFP measures for 2009. Therefore, the final panel dataset we can apply to measure the effect of R&D support program covers 2009-2014. Beside all these limitations, lagging outcome TFP measures to estimate the effect of R&D subsidies leads to missing observations in the related measurement. Future studies can implement the analysis on different contexts and subsequently datasets, taking into account the specific institutional considerations.

One other restriction is the limited information about the selection procedures and the technical and financial scores related to applications and R&D projects. Therefore, we could not access the ranking of projects for subsidized and non-subsidized (in this case rejected) applicants.

If such information was available, the Regression Discontinuity (RD) method (used in studies such as De Blasio et al., 2009; Bronzini et al., 2014; Cerqua & Pellegrini, 2014; Wang et al., 2015, Bronzini & Piselli, 2016; Dechezlepretre et al., 2016) could have been a better choice instead of the PSM methodology.

Another main limitation of the research similar to many other studies using matching techniques, is assuming that the selection procedure and factors are observable. However, this limitation becomes less serious as the analysis is carried out in a particular context (Province of Trento). The place-based context may reduce the effect of unobservables in comparison with nation-wide programs. The policy's local dimension allows for the removal of unobserved heterogeneity among private firms in comparison with the R&D programs nationwide in which the recipients and non-recipients are less similar.

One further main limitation of this essay is relaxing the assumption of R&D spillover effects to satisfy SUTVA property in implementation treatment impact evaluation. This restriction can get more serious in ICT industry with more dynamics and interactions between firms, as one of the main sectors this study has focused on. The context of this study may also reinforce this problem as spatial closure can increase network effects. Moreover, technological spillovers inside manufacturing and ICT sectors can also affect the analysis. On the other hand, if we can assume the new technological opportunities intensity and probability of collaboration in R&D is less different for the firms because of the regional vicinity, this can mollify ignoring the spillover effect on measuring the effect of R&D subsidies on the targeted outcome. Next chapter's empirical analysis puts effort to overcome the two former limitations; the effect of unobservable factors and spillovers effect.

In a more practical perspective, the presence of mixed findings makes it unfeasible to suggest a fit-to-all policy implications. However, the ex-post empirical evaluation provides information about the causal effects of R&D subsidies on growth for different sectors in different time spans. Finally, focusing on the channels and mechanisms through which R&D subsidies may influence R&D effort, R&D output and spillovers and ultimately firms' relative efficiency and technological frontier progress can be a complementary to the empirical policy causal effect evaluation.

Chapter 4:

Estimation of a Public R&D Policy (Program) Structural Model

Abstract

The empirical studies in public R&D subsidies evaluation, using econometric methods usually focus to measure only the magnitude and direction of the net causal effects of innovation policies. This leads to lack of explanation for the mechanism through which public subsidies allocated by the social planner may affect private R&D investment. Previous chapter measured the effect of R&D subsidies on a target outcome variable using non-parametric propensity score matching estimators, presuming neither effect of unobservable factors on selection and outcome, nor spillover effects. However, the method took advantage of not assuming any predefined structure for application, selection and investment procedures.

Modeling the R&D policy stages using a structural model which explains the interactions between the private firm as the agent and the public agency can shed light on the influence of different factors such as firms' characteristics on the subsidization process. This study reviews, benchmarks and empirically modifies a structural model for evaluation of targeted R&D subsidies.

The model takes into account the spillover effects as the main criteria for social planner in allocating subsidy rates for different R&D projects. Furthermore, the model theoretically and econometrically identifies different stages of application decision, R&D subsidies allocation and R&D investment decision. The local institutional context changes the settings related to the estimations. Data applied to estimate the model, refers to place-based R&D subsidies allocated to R&D doing firms and firms' characteristics provided by ISPAT office in province of Trento, Italy.

The context and dataset features allow for different empirical modifications with respect to the benchmark model applied. The results determine the effect of firm (project) characteristics on all stages of the subsidization game. Size, age, exporting status, board size and sector are main factors being investigated. The results show different firm characteristics influence the stages and mechanisms of R&D subsidies allocation. Moreover, on average there is a crowding out effect for R&D grants, while half of the amount of private spending on R&D will spill over the network.

1. Introduction and theoretical background

First chapter has extensively discussed the need for R&D public policies. Direct subsidies, tax credits, prizing and procurement contracts , beside intellectual property right (IPR: patent length design) are required as industrial policies to deal with the market failure caused by private (business) underinvestment in innovation (R&D) input. The R&D investment by private entities is usually less than the socially optimum expected amount. (Mansfield et al., 1986; Jones and Williams; 1997, Martin, 2002; Griliches, 2007). One main cause can be spillover effects discussed in section 1 of Chapter 1. Additional R&D projects carried out by private business firms may spill out in the network. Imitating and using the knowledge as the public good generated by R&D activities can benefit society and increase the social rate of return of R&D activities. However, if the firm cannot sufficiently appropriate profits out of R&D project due to spillovers effect and imitation of R&D output by rivals, the firm would not undertake additional R&D expenditures. The government as the responsible body to maximize the social welfare, designs and allocates incentives to encourage private firms to spend more on innovation. Furthermore, the social planner is assumed to be audited and criticized by the society, media and other political parties for efficient and effective allocation of the resources. Impact evaluation of R&D policies takes place in this context.

Chapter 1 and 2 explained the main challenges related to the measurement of R&D policy effect on targeted outcomes. The methodologies used to carry out the estimation of the effects and their advantages and drawbacks were also discussed. Moreover, the chapters provided a detailed literature review of studies evaluating the effect of R&D subsidies on R&D input additionality, beside R&D output and behavioral additionality and some other outcome variables particularly TFP change. The mixed and heterogenous findings of evaluation studies and the need for models explaining the channels of the effect have been addressed.

Afterwards, Chapter 3 measured the causal effect of a place-based R&D subsidies program using a quasi-experimental setting. However, the methodology used had limitations on considering unobservables' impact on R&D subsidies allocation and spillover effects. This chapter in order to measure subsidies' impact on R&D investment, applies another approach in order to tackle the discussed limitations. Structural modeling approach focuses on the interactions and mechanisms of different stages of R&D support and its effect process.

Effect of firms' characteristics on the mechanisms through which the policy affects the outcome, is the focus of estimations by the structural model. One main important characteristic widely addressed and investigated in empirical studies related to R&D activities and R&D policy is size. Size is the core point of Schumpeterian hypothesis and many studies have investigated the effect of firm size on innovation activities (see tables and content of the sections related to empirical literature review in chapter 1 and 2). As long as larger firms are more capable of managing the risks of R&D activity in imperfect markets, the R&D effort increases proportionally with the size of the firm following the hypothesis based on Schumpeter's second theoretical modification about the role of the size in innovation (1943).

Moreover, age has also been pointed out by Schumpeter in developing his primary hypothesis quoted in 'The theory of economic development' (1934), identifying the new firm as the motive for innovation. Later, in 'Socialism, capitalism and democracy' (1943), the hypothesis changes in the sense that the established firm (the older incumbent and probably with a higher share in the market) is the one responsible for technological progress. Age has been considered as one main characteristics in empirical studies related to innovation activity (see the content and tables in section related to empirical literature review in chapter 1 and 2). Other variables such as sales, export, previous R&D projects and etc. have been considered among firm characteristics influencing the innovative activity . Structural models using a system of equations, can measure the effect of these explanatory factors on different stages of an R&D program. R&D program stages usually consist of participation decision (self-selection), evaluation of R&D project to assign a subsidy rate (selection) and firm's decision about R&D expenditure (investment).

Levin and Reiss (1988) in their seminal work of structural empirical modeling in economics of innovation, have analyzed R&D policies when the returns to R&D expenditure are imperfectly appropriable because of existence of spillovers and the endogenous market structure. The R&D model is framed by distinguishing the process R&D and costs, product R&D and demand creation while assuming spillover. The equilibrium for R spending and D spending by the firm is defined by firm's profit maximization equation considering first-order conditions and free-entry equation. Furthermore, they empirically estimate the theoretical model using survey data and show the effect of differences in technological opportunity on both process and product R&D. The results make a distinction between extent of the spillovers and the productivity of spillovers which describe why for example firms in electronics industry perform large amounts of R&D even if there is a high level of spillovers in the industry.

Wallsten (2000) proposes a structural model to evaluate the effects of government-industry R&D programs on private R&D for the case of the Small Business Innovation Research program (SBIR) in U.S. In addition to a simple OLS while log of employment is the dependent variable, he uses simultaneous equation systems and instrumental variable to control the endogeneity of the R&D grants in another step. This instrumentation is involved in equations for funding allocation process in two stages. In case a firm is awarded in the first stage, then it is eligible to apply in a second phase for the subsidy. The agency's funding decision for both stages is also defined. The dependent variables in the three-staged least squares are number of phase 1 and 2 awards and log of employment. The study reveals that in the OLS regression the employment is correlated with the grants, where as in the structural analysis this is not the fact. This shows the importance of control for endogeneity in R&D program's evaluation. Although, the analysis done by Wallsten is called a structural analysis, neither it defines the channels through which public grants affect on private R&D, nor deals with spillovers of R&D expenditure.

Knowledge spillover of innovation projects must be taken into account in innovation policy studies as it is supposed to be a main public authority's criteria to decide for the level of subsidy allocated to a specific project. Those policy evaluation studies ruling out spillover effects (such as the method used in previous chapter), assume Stable Unit Treatment Assumption (SUTVA) defined for the first time by Rubin (1973), i.e. R&D outcome of one firm is not affected by the treatment offered to another firm in the population. Although SUTVA assumption is fundamental for causal analysis, however, in recent years, researchers in political science, economics and sociology have extensively devoted attention to the violation of the assumption (Sinclair et al., 2012).

Studies applying structural models can be linked to the literature on principle-agent as well. There is a public authority as the principle which interacts over R&D project incentive allocation process with the firms as the agents. Reiss and Wolak (2007) discuss principal-agent contracting models in which regulator attempts to make a balance between two contradictory goals of recovering all incurred costs of the firm and provision of incentives for the firm to efficiently produce under the assumption of incomplete information, which means the agent has private information about its production process, unobserved by the agency and econometrician.

The models explaining R&D activity takes either deterministic or stochastic form. Deterministic models using a static framework, allow to trace the R&D relationship with other factors and market structure variables. Stochastic models based on the uncertain nature of R&D activity, form the model and equations by assuming for instance innovation and input or output spillovers follow a stochastic pattern (Athey and Schmutzler, 1995; Martin, 2002). The model in this essay follow a static pattern, while determinants of the model can take random form.

This study benchmarks the structural model by Takalao, Tanayam and Toivanen (2013) and models and estimates a subsidy program as a four-staged game of incomplete information between a firm with an R&D project and the public agency. There is a perfect Nash Bayesian equilibrium for the model assuming specific functional forms for players' pay-offs. The model proposes a framework to measure the social value of R&D subsidies and the effect of the subsidies on the authority and the firms investing in R&D, in addition to the effect of firm characteristics on these variables. The parameters of the firms' and agency's objective functions and firms' application cost function are also estimated to measure the social rate of return, i.e. spillover rate of return to R&D subsidies. In the reference model expected welfare effects of individual subsidies and the whole subsidy program are estimated as well.

In the model, spillover level is a component of agency's utility maximization equation. Finding the solution of the equilibrium for agency and the agent simultaneously, spillover rate generated by the amount of private investment in R&D is measured. This in parallel ties to the amount of the grants allocated by the social planner to the rate of spillover each individual applicant's R&D investment is expected to generate. Consequently, the spillover rate will be measured by knowing the optimal amount of incentive decided by the authority and the coefficients of this relationship are the effect of characteristics of the R&D project on spillover.

Another feature of the model proposed by Takalo et al. (2013), following the idea of Gonzalez et al. (2005) is taking into account the application cost, and consequently application decision by the firms related to the entry cost. To econometrically estimate the theoretical model, Takalo et al. (2013) use detailed data about grants assigned by the Finnish authority for R&D subsidies provided by public agency called Tekes (the Finnish Funding Agency for Technology and Innovation), and also firm-level data for 14567 firms from a for-profit company responsible for collection, standardization and selling firm-specific quantitative information. The observations used to estimate the different equations of subsidy rate, application, R&D investment and grading process are different as the firms involved in each part of estimation are not always the same firms.

The R&D investment equation takes a pre-defined theoretical form which is independent of the context. R&D application and the selection process resemble in our context with the Finnish context of Takalo et al.'s study. Although The Finnish public agency (Tekes') deals with subsidies nation-wide, however, subsidies allocation process in general perspective resembles APIAE's. Firms self-select and apply for grants and the public agency evaluates the applications on technical and financial aspects and decides on specific subsidy rates for each project. The subsidies are injected into projects within different installments in both contexts. Moreover, the main focus of both agencies are R&D support for SMEs. Tekes grants low-interest and capital loans besides subsidies, however, as long as calculating the value of these instruments is complicated Takalo et al. have pooled all instruments together as public subsidies. This study applies data on R&D subsidy allocation by APIAE and firm-level data provided by ISPAT[100]. Datasets used in the analysis are partially described and discussed in Chapter 3 and current chapter as well.

The framework is basically a game theoretical model to be estimated econometrically. The customized simplified model describes processes related to the firms' R&D investment and subsidy application decision and subsequently the grant allocation by the local authority. The parameters of the firms' and the agency's objective functions and the firms' application function are estimated using R&D project-level data. These parameters can be applied to calculate the social rate of return and the treatment effect of the subsidy program.

The data on firms' and projects' characteristics and balance sheets is provided by ISPAT dataset available in provincial statistical office. Datasets compiled and analyzed in different studies are mainly cross-sectional panel or time series data. Levels of aggregation include firm, industry and country (national) levels. Moreover, laboratories, research institutions, universities and non-profit entities are also among the different levels of analysis in some minor studies. In this

[100] Statistical Institute of Province of Trento: In Italian (Istituto di Statistica della Provincia di Trento) is the general statistical directorate of the province and the provincial counterpart of ISTAT, the Italian national statistical institution.

essay a cross-sectional panel has been used to estimate the model. A structural model for R&D public subsidies is presented to measure the effect of the policy on private R&D at the firm-level using the dataset related to firms as agents and the agency authenticated to allocate subsidies in the autonomous province of Trento in Italy. In the following, chapter 2 defines the model, chapter 3 represents data and dataset applied. Results are discussed in chapter 4 and finally chapter 5 concludes.

2. The Reference Model

2.1 Model definition based on Takalo, Tanayama and Toivanen model (2013)

Model is a four-stage game of incomplete information between a firm with an R&D project and the public authority (agency). In stage 0, the types of the projects or firms or applicants (all used interchangeably in this chapter) are determined. The type of project i, $t_i^F = (\varepsilon_i, \nu_i) \in \Re^2$, and the agency's type pertained to the project i, $t_i^A = (\eta_i, \omega_{ic}, \omega_{im}) \in \Re^3$, are drawn from common knowledge (joint) distribution. t_i^A and t_i^F define the expected values of the project i, for the agency and the firm respectively. On the contrary to the setting in previous chapter, unobservable factors are considered in the econometric model.

In stage 1, the firm decides whether to apply for the subsidy or not. The firm does not know exactly how the agency evaluates the application. Hence, symmetric incomplete information for the agency's type holds while the firm's type is common knowledge.

In stage 2, the agency assesses the projects and learns the project's type. Consequently, agency allocate a subsidy rate, s_i , $s_i \in [0, \bar{s}_i]$, which is the share of the R&D project's total cost covered by the agency. $\bar{s}_i$ is the upper bound for the subsidy rate specified for any applicant, $\bar{s}_i \leq 1$. It is assumed that non applicants cannot receive the subsidy and the agency or public authority does not bind to budget constraint.

In stage 3, the firm decides on the amount of the R&D investment, R_i, $R_i \in \Re^+$ with or without the subsidy. No fixed cost for the investment or any constraints on the investment are assumed. The subsidy amount is then the subsidy rate multiplied by the investment amount, $s_i R_i$. The model assumes that the subsidy cannot be misused and there is no moral hazard or free-riding.

The game proposed is a perfect Bayesian equilibria. Firstly, a potential applicant has an expectation of the agency's strategies which are contingent to the type of the agency in stage 2.

The agency's and firm's strategies are sequentially rational. As the posterior belief concerning the agency's type is inconsequential after the subsidy allocation, solving the model equations starts from the firm's maximization problem in stage 3. Players' payoffs have been modeled by specific functional forms due to model empirical estimation by using data in derived equations.

In the following the main equations of different stages of the model and the solution of the model are discussed.

2.2. Objective function of the firm

The firm's expected profits from project *i* is specified as:

$$\Pi(R_i, s_i, X_i, \varepsilon_i) = \exp(X_i\beta + \varepsilon_i)\, lnR_i - (1 - s_i)R_i \tag{1}$$

where R_i is the investment in R&D by firm i; s_i is the share and contribution of the public agency to an admitted project; X_i is a vector of observable firm characteristics and β is a vector of parameters to be estimated. ε_i is profit random shock which is related to firm *i*'s type. As implied by the utility function there is decreasing returns to scale for firm's R&D technology. This definition of firm's objective function makes it globally concave and therefore the optimal investment R_i is determined by maximizing the profit which is shown as the first-order condition in the following which gives $R_i(s_i)$ as a function of the subsidy rate:

$$R_i = \frac{exp(X_i\beta + \varepsilon_i)}{1 - s_i} \tag{2}$$

This equation shows how subsidy rate affects the profit margin. The economic interpretation of ε_i explains how positive shock to marginal profitability due to unobservable factors leads to a higher investment in innovation. Referred to equation (2), if public authority covers total expenditures of a project (%100 of the costs which means $s_i = 1$), then the firm invest as much as possible. However, if the agency does not accept to cover the project (which means a subsidy rate of 0) then the firm invests an amount equal to $\exp(X_i\beta + \varepsilon_i)$ which is the amount the firm would plan to invest had not even been allocated the subsidy. The additional investment by being granted can be calculated as: $Investment\ amount\ being\ awarded\ the\ grant - investment\ withouth\ subsidies\ = \frac{exp(X_i\beta+\varepsilon_i)}{1-s_i} - exp(X_i\beta + \varepsilon_i) = \frac{s_i}{1-s_i} . exp(X_i\beta + \varepsilon_i)$.

As noticed in the previous chapter, the expenditures eligible for the support consist of a) expenses for employees including the expenses of the owner and partners; b) spending for research contracts, skilled technicians and patents; c) additional expenses for market search; d) other operating costs, and e) costs of tools and equipment. However, the data on firms' R&D expenditures in our setting is the total planned R&D investments reported by the firms. Moreover, it is worth to restate that the fixed cost of R&D projects are assumed zero as the firms are R&D doing firms with an established R&D business unit.

2.3 Agency utility function

The agency's expected utility from an applicant's project *i* is the sum of values of spillover level, employment rate and firm's expected profit minus the opportunity cost of the grants which agency devotes to projects and application screening and project monitoring costs. The employment rate is considered in the investment returns for the firms which are mentioned in the profit function of the firm. The utility function of the firm is as equation (3):

$$U(R_i(s_i), s_i, X_i, Z_i, \varepsilon_i, \eta_i) = V(R_i(s_i), Z_i, \eta_i) + \Pi(R_i(s_i), s_i, X_i, \varepsilon_i) - g s_i R_i(s_i) - F_i \qquad (3)$$

where, F_i is the total cost of application screening, and g is the constant opportunity cost of agency resources for example cost of funds which are taxed. $V(\,)$ is the spillover level as a policy objective for the agency beside a goal of the policy maker in the theoretical literature. The public authority is seeking for higher levels of spillover to maximize the competency of the firms. $V(\,)$ can consist of both positive and negative externalities. Positive externalities include consumer surplus, technological spillovers to other firms and negative externalities may include cost-duplication, business-stealing effects and negative environmentally effects (see section 1.2 of chapter one). However it is widely accepted in theory that positive externalities of R&D investment outperform the negative ones.

η_i is the random shock to the spillovers from project *i*. This is observed by the agency only after that application and evaluation take place in stage 2, but is unobserved by the applicant and the econometrician in stage 1. It means the applicant is uncertain about how the agency assesses the project's potential to generate spillovers for the agency's civil servants.

The term Z_i in $V(\,)$ is a vector of observable firm characteristics which contains the same element of X_i , but also includes the evaluation main factors that technical committee assign to the projects based on their evaluation criteria. In the main model, the agency grades the project's quality in two dimensions which are included in Z_i, observed by the agency and the econometrician but not by the firm. The remaining parts of the agency's type, ω_{ic} and ω_{im}, are random shocks to the evaluation outcome of project i, in the grading dimensions c and m, respectively, and are proxies for technical challenge and market risk of the projects. It is assumed in the model that grading process, its parameters, and the distribution of $\omega_{ij}, j \in \{c, m\}$ are common knowledge which let the firms anticipate the probability of getting a particular grade in each grading dimension conditional on observables.

Related to our context, the goals of provincial law LP 6/99 articles 5 and 19 directly link to investment in applied research and diffusion of scientific research in the province. Moreover, the province is expected to increase business *efficiency and effectiveness* through "granting aids and credit facilities to firms, in all sectors apart from agriculture.". Therefore, firms' profit, beside the spillover generated to benefit the society can be included into the agency's profit function.

2.4 Optimal subsidy rate

To calculate the optimal rate of subsidy in an estimable model, a linear relationship between subsidy rate[101] and firms and projects characteristics is predefined as the following:

$$\frac{\partial V}{\partial R} = Z_i \lambda + \eta_i \tag{4}$$

where λ is a vector of parameters which links the projects' characteristics with spillover rate. Later it will be shown that this vector of λ represents spillover effects. η_i, as determined before is the shock to spillover rate.

The optimum s_i to make the agency's utility maximized takes into account the firms' profit maximization of R&D investments (equations 1 and 2) and the spillover rate assumption (equation 4).

Deriving equation (3) with respect to s_i we have:

$$\frac{\partial u}{\partial s_i} = \left[\frac{\partial v}{\partial R_i} \cdot \frac{\partial R_i}{\partial s_i} \right] + \left[\frac{\partial \pi}{\partial R_i} . \frac{\partial R_i}{\partial s_i} \right] + \frac{\partial \pi}{\partial s_i} - gR_i - gs_i \frac{\partial R_i}{\partial s_i}$$

Now using envelope theorem and substituting R_i from equation (2) and $\frac{\partial v}{\partial R_i}$ from equation (4), we find s_i^*:

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[101] Spillover per dollar of R&D investment: $\frac{\partial V}{\partial R}$

$$\frac{\partial u}{\partial s_i} = \left[(Z_i\lambda + \eta_i).\frac{exp(X_i\beta+\varepsilon_i)}{(1-s_i)^2}\right] + \left[\left\{\frac{exp(X_i\beta+\varepsilon_i)}{\frac{exp(X_i\beta+\varepsilon_i)}{(1-s_i)}} - (1-s_i)\right\}. \frac{exp(X_i\beta+\varepsilon_i)}{(1-s_i)^2}\right] + \frac{exp(X_i\beta+\varepsilon_i)}{(1-s_i)} - g\ \frac{exp(X_i\beta+\varepsilon_i)}{(1-s_i)} - gs_i\ \frac{exp(X_i\beta+\varepsilon_i)}{(1-s_i)^2} = \left[(Z_i\lambda + \eta_i).\frac{exp(X_i\beta+\varepsilon_i)}{(1-s_i)^2}\right] + [\{(1-s_i) - (1-s_i)\}.(\frac{exp(X_i\beta+\varepsilon_i)}{(1-s_i)^2}] + \frac{exp(X_i\beta+\varepsilon_i)}{(1-s_i)} - g\frac{exp(X_i\beta+\varepsilon_i)}{(1-s_i)} - g\ s_i\frac{exp(X_i\beta+\varepsilon_i)}{(1-s_i)^2}$$

After cancelling out the common terms and multiplying both sides of the equation by $(1-\mathrm{s_i})^2$ we have:

$$0 = Z_i\lambda + \eta_i + (1-s_i) - g(1-s_i) - gs_i = Z_i\lambda + \eta_i + 1 - s_i - g + gs_i - gs_i = 1 - g + Z_i\lambda + \eta_i - s_i$$

which results in equation (5).

$$s_i^* = 1 - g + Z_i\lambda + \eta_i \qquad (5)$$

Equation (5) is verified as the maximum. Obviously, the higher the shadow cost of public funds (g), the lower the subsidy rate becomes. Profitability shock of the R&D projects does not have effect on the amount of the grants to be allocated.

Measures of spillover parameters λ and the variance of η_i are attained by estimating equation (5) using the data for successful applicants. The vector of λ , shows how much the agency values the spillover generated from each Euro of R&D by project i , in addition to the profit gained by the firm. The spillovers level can be measured by inserting λ into the equation of spillover obtained from integration of equation (4):

$$V(R_i(s_i), Z_i, \eta_i) = (Z_i\lambda + \eta_i)R_i \qquad (6)$$

The constant of the integration is 0 because spillovers are generated only due to positive investment in R&D. The vector of λ determines spillover effects by each project, i.e. *the estimated marginal effect of the factors influencing the subsidy rate allocated to a project, is the spillover rate (λ).*

2.5 The firm's belief, application costs and application decision equations

The firm will apply for the subsidy, if the expected profits out of the application are at least, as large as the profit of the project without applying. The expected profit obtained from application is calculated based on the firm's beliefs about the agency's evaluation of the project. The agency's evaluation of project i, depends on its type, $t_i^A = (\eta_i, \omega_{ic}, \omega_{im})$ unknown to the firm prior to the application. Therefore, the firm i has a belief about η_i. Let $\phi(\eta_i)$ define the belief and $\Phi(\eta_i)$ be the cumulative distribution function (cdf) of the belief. In addition, let $p_{ijh}(\omega_{ij})$ denote the probability that a firm's application is graded $h \in \{1, \dots, 5\}$ in grading dimension $j \in \{c, m\}$. To formulate the application decision equation, an application cost is assumed as in equation (7):

$$K_i = exp(Y_i\theta + \nu_i) \tag{7}$$

where Y_i is a vector of observable firm characteristics and θ is a vector of parameters to be estimated as application costs parameters. ν_i, the error term, is the application costs random shock observed by the firm and the agency but not the econometrician. Application costs are a component of F_i in equation (3).

The application decision rule proposed is shown in equation (8). The subscript i and the argument ω_{ij} are dropped for simplicity:

$$d = 1\left\{\sum_{ch=1}^{5}\sum_{mh=1}^{5} p_{ch}p_{mh}\left\{\phi\left(\underline{\eta}(ch,mh)\right)\prod(R(0),0) + \int_{\underline{\eta}(ch,mh)}^{\eta(ch,mh)} \prod\Big(R\big(s(ch,mh,\eta)\big), s(ch,mh,\eta)\Big)\phi(\eta)d\eta + [1-\phi(\bar{\eta}(ch,mh))]\prod(R(\bar{s}),\bar{s})\right\} - \prod(R(0),0) - K \geq 0\right\} \tag{8}$$

where d_i is an indicator function that takes value 1, if a firm applies for a subsidy and 0 otherwise. In equation (8), the summations are over the potential grading outcomes. The first term in the inner braces is the expected profit in case the application is rejected. A rejection occurs when $\eta_i \leq \underline{\eta_i} \equiv g - 1 - Z_i\lambda$ (where Z_i includes the grades ch and mh), that is, with probability $\Phi(\overline{\eta_i})$. Correspondingly, the third term demonstrates the expected profits with a maximal subsidy rate, which the firm obtains with probability $1 - \Phi(\underline{\eta_i} \equiv \overline{s_i} + g - 1 - Z_i\lambda)$. The second term is then the expected profit where $\eta_i \in (\underline{\eta_i}, \overline{\eta_i})$ and the firm receives the optimal interior subsidy rate given by equation (5). The two last terms capture the opportunity cost of application. Beside the application costs K_i, the firm takes into account the possibility of executing the project without a subsidy, where the project yields $\Pi(R_i(0), 0)$ (Takalo et al., 2013).

In our context, the R&D subsidies allocation procedure takes three main forms of automatic, evaluative and negotiating procedures. As long as all the firms applying for R&D subsides in automatic procedures expect the subsidies allocation ex ante and are capable of estimating the subsidies rate, therefore the perceived belief of the firms about the subsidies are determined per se. In addition, our context is local which reduces the level of uncertainty about the decision of public agency in contrary to the national context which Tekes allocates funds. On the other hand, no access to the detailed technical and financial rankings of R&D projects in evaluative and negotiating procedures, limited us in estimating $\phi\left(\underline{\eta}(ch, mh)\right)$. However, the terms related to perceived expectations and beliefs have been discussed in order to show how the application decision equation is formed. Finally we can equally estimate the simplified application decision to investigate the firms' characteristics effect on application decision.

2.6 Equilibrium

The game has a unique Perfect Nash Bayesian Equilibrium which let the model be econometrically estimated. The perfect Bayesian Equilibrium consists of four components: (a) a firm's system of belief about the R&D project evaluation process including $p_{ijh}(\omega_{ij})$, $j \in \{c, m\}$, $h \in \{1, \dots, 5\}$, and $\Phi(\overline{\eta_i})$ that describes a common distribution of how the agency evaluates the firm's project; (b) the firm's decision whether to apply for a subsidy, $d_i \in \{0,1\}$, given its beliefs; (c) the subsidy rate decided by the agency $s_i = s_i^* d_i$ which is the subsidy rate granted to the project i, and (d) firm's investment rule $R_i^*(s_i)$.

In order to prove the existence of a unique equilibrium, Takalo et al. (2013) show that equation (3) which defines the agency's utility function, $U(R^*(s), s)$ is concave and have a maximum point satisfying $\frac{\partial \pi}{\partial R} = 0$, while the profit function for firm's R&D investment is optimized simultaneously. There is an equilibrium where d_i is given by equation (8), and $s_i = s_i^* d_i$ where d_i is the acceptance or rejection status of project i and $\mathrm{R_i(s_i)}$, the R&D investment is identified by equation (2).

The model like other counterparts in industrial organization literature has limitations and drawbacks. As firms are monitored after being allocated the R&D subsidies, it is assumed that no moral hazard by the firms happens. This assumption also holds in our context as APIAE has assigned a department due to monitoring the project's progress. Moreover, strong assumptions of no financial constraints (for the firms and agency) and fixed R&D costs (for the firms) hold. Fixed R&D costs can be left aside as long as firms with new R&D projects are assumed to do internal R&D, operating in the region[102].

Furthermore, to investigate whether firms are financially restricted, one can run the ideal test of Hall. Firms are offered a hypothetical payment and asked to choose between alternatives of use. If they select additional innovation projects, they must have had some unexploited investment opportunities that were not profitable using more costly external finance (Hottenrott & Peters, 2012). The profit function of the firm can take other forms than logarithmic returns to R&D assumed in this model. The effect of subsidy rate on profit is assumed linear as $k = 1$ for $(1 - S_i)^k$ in equation (1). If the null hypothesis of $k = 1$ cannot be rejected then there is nonlinear effect of subsidy rate on additionality.

In the following sections, after describing the data applied to estimate the model, the econometric model will be modified and framed, taking into account the institutional context (related to LP 6/99 in Province of Trento), the data specifications and restrictions and estimation settings. Then the constructed dataset gets applied into the econometric model and results obtained are discussed.

3. Data and Variables

The data on R&D subsidies rates for R&D projects are provided by APIAE. The data about firms' projects and the contribution to the projects are for a period between 2005 to 2011. The dataset consists of detailed information on the projects excluding projects' technical information, and the APIAE's subsidy allocation decision. A part of the data on firm-level characteristics and R&D investment are provided by ISPAT office in Autonomous Province of Trento, which is a provincial equivalent of ISTAT. In addition, ISPAT provides the dataset ASIA[103] which consists of the information on firms' employment. ASIA complete dataset covers the period of 2000 to 2011. The other part of the data comes from PITAGORA database of Cerved Group.

[102] Even firms without internal R&D may externally and collaboratively do R&D activity.
[103] Archivio Statistico delle Imprese Attive

After polishing and cleaning the dataset from all missing values and outliers, the final dataset obtains 293 observations at firm level.[104] Figure (1) depicts total number of observations which consist of the aggregation of all firms which have responded to R&D survey[105] (247 observations) and the firms which have been provided R&D subsidies by APIAE within the period from 2008 to 2010 (94 observations). The unit of analysis is firm-year (project-year in equations related to R&D projects). The firms' responses to R&D questionnaire (RS survey) are collected by ISPAT, while the data for R&D subsidies are collected from APIAE. The data on firms' characteristics are extracted from PITAGORA and ASIA datasets. The common area in figure (1) consists of 48 firms; i.e. 48 firms which have responded to R&S survey between 2008 to 2010 and have been subsidized for R&D projects in the same year.

The variables defining the observations are firms' responses to R&D questionnaire[106] (If the survey has been responded), the data on R&D subsidy assigned to accepted applications and finally the data on firms' characteristics. Table (1) describes the number of observations for each year with respect to R&D subsidies allocation and R&D survey response categories.

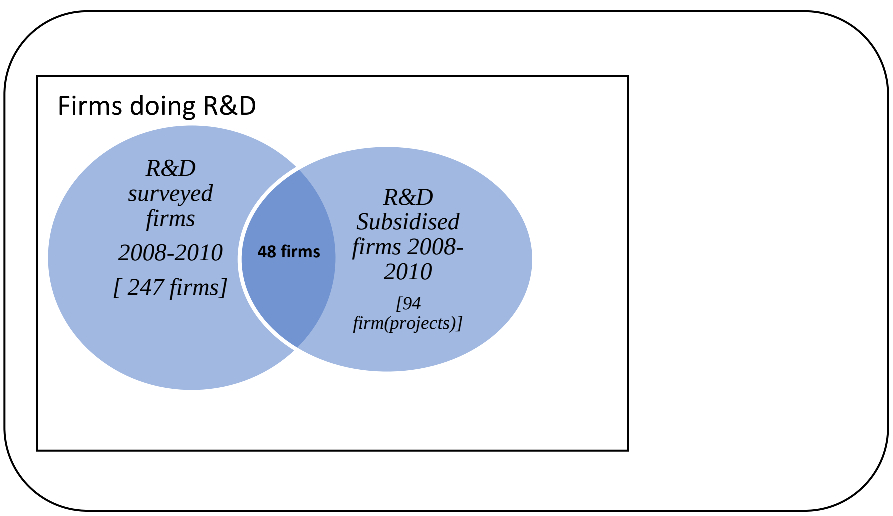

Figure 1. The datasets and observations Venn diagram

[104] The procedures to construct the final dataset from the primary dataset has been reviewed in Appendix (4.a).
[105] The Community Innovation Survey (CIS)
[106] CIS2008- CIS2009- CIS2010

Table 1. Sample description: Number of R&D subsidized (treated) firms and R&D Innovation Survey respondents

Year	All firms	R&D Subsidized	R&D Survey Respondents	Subsidized and R&D Respondent
2008	92	26	82	16
2009	104	33	84	13
2010	97	35	81	19
Total	**293**	**94**	**247**	**48**

Source: Community Innovation Survey (CIS) provided by ISPAT and dataset on grants assigned for applied research projects provided by APIAE

In the following table (2), all variables being used in econometric estimations of the model are described. The description has been shown for all potential applicants (All the firms being targeted for R&D survey), subsidized firms and other firms which have not benefited from subsidies (either by not applying or not being allocated). Later in the section related to estimation of econometric equations, we will discuss about the variables applied in each equation.

Not surprisingly, subsidized firms are on average smaller than non-subsidized, while the age does not differ between two group of the firms. The largest subsidized firm has 450 employees as non SMEs can also benefit from the incentives. Subsidized firms have a higher sale-to-employee amount with respect to their non-subsidized counterparts. The maximum number of board size of a company is 8 members and the minimum is 1. Nearly, half of the firms in all categories are exporting firms. At the same time more than 60% of the firms in all categories are SMEs. The annual actual R&D expenditure (the amount reported) is also shown in the table. As expected, the amount is higher for R&D subsidized firms in comparison to those not using R&D grants.

The data on subsidized firms show that subsidized firms have planned to do R&D (based on their primary applications) on average about 1.3 million euros. The maximum planned project investment is expected to be around 9 million Euros. Moreover, the supported firms have had one previous allocation on average, while the maximum number of allocations reaches to six assignments. The public agency (APIAE) have covered 52% of the total costs of R&D projects in our sample, while the maximum subsidy rate allocated attains 80%.

Table 2. Descriptive statistics of variables applied in estimation of the structural model

	All potential applicants				Subsidized applicants				Non-Subsidized firms			
	Mean	Std. Dev.	Min.	Max	Mean	Std. Dev.	Min	Max	Mean	Std. Dev	Min.	Max.
Size	81.29	172.26	1	1637	57.07	84.90	1	450	92.74	199.91	1	1637
Age	18.34	14.18	0	62	18.40	14.89	0	62	18.32	13.86	1	53
Sales per employee	310,177.9	808053.3	0	9,042,264	399,056.2	1,227,169	0	9,042,264	268,195.2	500,077.9	0	5,198,274
Board Size	1.23	0.92	1	8	1.12	0.39	1	3	1.28	1.08	1	8
Exporter (Dummy)	0.52	0.50	0	1	0.53	0.50	0	1	0.51	0.50	0	1
SME	0.64	0.47	0	1	0.68	0.46	0	1	0.62	0.48	0	1
R&D Expenditures (year)	593,773.3	820,240.6	4,000	5,521,000	739,562.5	815,468.4	7,000	3,351,000	558,608	819,542.6	4,000	5,521,000
Planned R&D investment					1,298,585	1530747	48,559	8,823,200				
Number of Previous Applications					0.91	1.52	0	6				
Subsidy rate					0.52	0.21	0.05	0.80				
Expected (perceived) subsidy rate					0.54	0.22	0.05	0.80				
Subsidy amount					658,601.2	829126	7,233.9	5,606,350				
Evaluation method					2.06	0.68	1**	3				
Number of observation	293				94				199			

* Amounts are in €

** Evaluation procedures: Automatic:1, Evaluative:2, Negotiating:3

The projects have been installed on average an amount of 658 thousands Euros with a standard deviation of 829126 Euros. The grants allocated ranges between 7,234 to 5,606,350 Euros. The allocation procedure tends more towards evaluative method as also described in previous chapter. In our representative sample the number of projects being granted by automatic, evaluative, and negotiating procedures are 19, 50 and 25 respectively.

Next section deals with the econometric transformation of the reference theoretical model and the application of the data on variables in each estimation referring to model equations.

4. Data implication, empirical strategy and econometric model

4.1. Data and variables implication and empirical strategy

Theoretical model of Takalo et al. (2013) as the reference is used to form an estimable econometric model based on the institutional settings. Statistical assumptions of the model are determined as well. Equations (2), (5) and (8) identifying R&D investment equation, subsidy rate decision equation and application decision equation are the fundamental equations of the theoretical model. Econometric equations link to these equations with substantial empirical modifications regarding our context. Moreover, the equations form the unique Bayesian Nash Equilibrium.

Variables have been described and discussed in the previous section. However, the final decision on the use of different variables involved in each specific equation is pointed out in table (3). The variables size, age, sales per employee and exporting status are applied in all estimations. However, for size factor, log of the number of employees is applied into application decision and investment equations, while SME factor is involved into subsidy rate equation due to the effect on subsidy amount allocated according to table (1) in chapter three. The table shows contribution percentages of evaluation procedures based on size and the effect of the project.

SME definition is the one determined by EU and it is assumed in the model that a firm will not deliberately change the size to be SME for probable higher subsidy, thus SME is considered as an exogenous variable. SME definition provided by EU represents enterprises with fewer than 250 employees or sales less than 40 million Euros or a balance sheet less than 27 million Euros. In the Italian context, the definition of SMEs does not always reflect the European Commission’s definition. However, in LP 6/99 SME definition is the one in line with EU definition.

Table 3. variables applied in equation estimations

Explanatory variable in the econometric estimations	***Application decision equation***	***Subsidy rate equation***	***R&D investment equation***
Age	●	●	●
Log of Employment	●	○	●
Sales/employee	●	○	●
SME	○	●	○
Exporter	●	●	●
Board Size	●	○	●
Industry dummies	●	●	●
Dependent variable	Dummy variable taking value 1 if the firm applies0 for subsidy, and 0 otherwise	Subsidy rate	R&D investment declared in CIS questionnaire
Sample	Potential applicants (Firms which does R&D according to their response to the CIS Survey)	Subsidized Applicants	Subsidized applicants who have responded to CIS survey at the same year of the application acceptance
Number of Observations	293	94	94 for planned investment and 48 for actual investment
Estimation	Probit model	OLS	OLS

● the involvement of the variable in the estimation of the equation ○: No involvement

In fact, 99.9% of Italian enterprises are micro, medium and small enterprises employing less than 250 employees.

The exponential logarithm of employees squared, $Ln(emp.)^{2}$, beside ${}^{Sales}/_{Employee}{}^{2}$ could have been taken into account for the estimations, to test the nonlinear correlation of related variables to the dependent variables. However, both these variables are excluded due to multicollinearity and high variance inflation factor (VIFs). Higher number of previous applications can be considered as more experience in completion of an application process because of learning from previous application procedures, and consequently expected lower cost for application. Therefore, the number of previous applications cannot take parts in application decision equation due to high correlation with subsidy rate in correlation matrix. The variable is not included in investment equation estimation as well, because once a firm is subsidized, spends the same R&D amount regardless of the frequency of being previously supported. Hence, the variable drops from our estimations.

Being an exporter, a firm can learn from exporting experience how to manage more effectively and efficiently the official and informal procedures for other types of interactions and transactions such as R&D subsidy application. On the other hand, the public agency probably expects an exporting firm to be more capable in accomplishing an R&D project. Therefore, being an exporter may influence agency's decision on subsidy rates. In addition, being an exporter implies less financial restrictions in spending on new projects including R&D projects. Export dummy is applied in all equations.

Industry sector dummies can arrive in all equation estimations. The sector classification is based on ateco 2007 economic activity coding. In the raw primary dataset there have been some industries with very low number of observations. We have kept those industries with at least one treatment happening inside. Table (4) shows the frequency of the observations and subsidies within each industry. The highest frequency of subsidies occur in manufacturing and ICT sectors.

Table 4. The number of subsidized and non-subsidized firms in different sectors

Sector	Non-subsidized	Subsidized
Manufacturing (C)	122	60
Construction (F)	5	7
Whole sale and retail trade, repair of motors (G)	9	1
ICT (J)	39	21
Scientific, technical and scientific activity (M)	24	5

Evaluation method due to high correlation to the subsidy rates is excluded from the spillover equation estimation. Board size is involved in the application decision equation and R&D spending decision. collective decision making by the board members can influence the application decision and the amount the firm would invest in R&D. The bigger the board is, the higher becomes the probability for conflicts over application decision and R&D investment (Erbetta et al., 2011). Therefore, we also take into account board side as a factor variable.

The sample used for application decision equation in the reference model includes all active firms while this study considers the firms which have been targeted by innovation survey. Hence, firms already doing R&D activities are considered as potential applicants. One different empirical feature of this chapter is that unlike Takalo et al. (2013) which consider all the firms in the country as potential applicants, we restrict the potential applicants to firms doing R&D and being targeted by RS survey. This does not challenge the estimation while it is assumed that there is no fixed R&D cost for R&D projects applications. In case the sample for potential applicants consists of all firms, the firm not having an R&D unit may spend the fixed cost for setting up R&D unit in order to apply for incentives. However, in this study the fixed set up cost is assumed to be zero, as all the potential applicants are the firms doing R&D.

4.2 Econometric equations

Equations to be econometrically estimated are formed based on the equations in the reference theoretical model. As previously mentioned this study skips estimation of grading equation as long the evaluation process is common knowledge and the dataset only includes the applications being allocated a subsidy, besides other potential applicants. The subsidy rate equation (5) which is the first-order condition of the public agency's optimization problem is repeated as the following for convenience:

$$s_i^* = 1 - g + Z_i\lambda + \eta_i \tag{9}$$

Actual amounts of s_i decided by APIAE for each firm-project are applied into the equation.[107] The explanatory variables are firm characteristics mentioned in table (5). Spillover parameter λ and the variance η_i are realized estimating equation (9). The vector λ measures the

[107] In the reference study s_i has values minimum 0 and maximum of {0.5, 0.6} or the optimal value of $\bar{s}_i$ as the subsidy rate. In our setting the subsidy rate ranges in an interval of [0.05, 0.80].

spillover rate which shows how much each dollar of R&D by firm i is valued by the public agency in addition to the effect of this spending on firm's profit. Integrating equation (4) we have $V(R_i(s_i), Z_i, \eta_i) = (Z_i\lambda + \eta_i)R_i$ which measures the spillover (not spillover rate) by inserting the estimated coefficients of λ and η_i.

Using equations (1), (2), (6) and some algebra following Takalo et al. (2013), equation (8) of the model for application decision gets simplified to:

$$d_i = 1\{X_i\beta - Y_i\theta + ln[-E(ln(1 - s_i))] \geq \nu_i - \varepsilon_i\} \quad (10)$$

where d_i is a dummy variable in an indicator function form. If the firm has applied for subsidy d_i gets value 1, otherwise it takes 0.

The s_i in the equation are the perceived shares which firms expect to obtain by APIAE before the realization of the actual grants' rates. An empirical feature of our study different from the reference model. In the reference model due to access to the pre-application perception of the firms on the grades their project would obtain after evaluation, they can measure equation (8) leading to estimation of the application cost function.

In our setting, we do not possess the data about the ex-ante belief of the firms over their applications. However, we have the data regarding the estimated prediction of the firms over the R&D project cost before application, beside the admissible amount estimated by the agency and finally the ascertained amount installed into the projects.

By calculating how much the contribution amount would have been assuming the estimated predicted amount of the project expenditures; we generate a new expected subsides rates which can be applied into the application decision equation. Although, the amount can be less precise than the actual belief system of the firms over applications, however, this simplify the model due to no requirement of technical and risk (in our setting the technical and financial) grades of the evaluation procedure. [108]

Moreover for future work, these expected amounts can be measured by a survey and investigation on firms' applications documents as the firms know the type of their projects based

[108] In order to measure expected subsidies, primarily A logic model based on the scheme of allocation related to table (1) in chapter 3, has been formed (appendix 4.b) It was an effort to describe the firm expected rate of subsidy before applying for the projects, however we do not use it in our estimations.

on specific criteria set by the agency. In other words, the firm knows per se whether the project falls into the category of automatic or non-automatic evaluation. This consequently leads to an expected s_i which has the possibility to be different than the actual subsidy. For instant, when a firm supposes that the project may be awarded a subsidy of 75 percent of contribution by APIAE and after the evaluation and allocation the rate turns out to be 60 percent, then the decision function must be estimated by $s_i = 0.75$, while the profit function must be estimated by $s_i = 0.6$.

According to the reference model, Equation (10) forms the first stage of a sample selection model, where the second stage is the firm's decision on R&D investment. In application decision equation parameters θ related to application costs are obtained by use of the estimation results of parameters β of the investment equation.

The final stage of the game is the R&D investment decision. The same as reference study, taking log of equation (2) yields equation (11):

$$ln\ R_i^*(s_i) = X_i\beta - \ln(1 - s_i) + \varepsilon_i \tag{11}$$

The firm decides how much to invest after finding out the subsidy rate. However, as the actual investment of the firm is not yet observed, the investment $R_i^*(s_i)$ is the planned R&D decision. In order to solve this problem, the planned R&D investment is applied to equation (11). The logic is that "an applicant strictly prefers proposing a budget based on a maximum subsidy rate over proposing any smaller amount and is indifferent between proposing that budget and any larger amount" (Takalo et al., 2013). Therefore, the applicant choose the investment amount assuming it would receive the maximum subsidy rate $\overline{s_\imath}$. The investment equation by some substitution and rearrangement is:

$$\ln[(1 - \overline{s_\imath})R_i^*(\overline{s_\imath})] = X_i\beta + \varepsilon_i \tag{12}$$

Equation (12) estimates β, which measures the effect of firm characteristics on the marginal profitability of R&D, beside the profitability shock ε_i. The dependent variable is the log of the R&D investment the firm plans to carry out. Explanatory variables in the investment equation are as mentioned in table (3).

In the reference model, the planned R&D has been used as dependent variable, therefore, the problem of endogeneity of subsidies in the investment equation does not make a problem. Even in cases when spillover shock η_i is correlated with ε_i , there would be no problem in estimation of the investment equation (12). As described in table (3), for the first stage of the self-selection model, we analyze the firms doing R&D, while for the second stage of R&D investment decision the sample would be the firms which have applied for R&D subsidy. In addition to planned investment, as long as we have the access to realized expenditures of the projects, we apply actual R&D expenditures as well. Estimation of investment equation using actual R&D investment, besides planned R&D investment is another empirical feature different from Takalo et al (2013).

4.3 Statistical Assumptions

This section reviews the main statistical assumptions according to the reference model. All unobservable error terms $(\varepsilon, \eta, \nu, \vartheta, \omega_j)$ are uncorrelated with observables. All shocks or error terms are assumed uncorrelated with other shocks. This assumption is different from the base model which consider application cost correlated with profit shock.[109] Relaxing of this assumption helps us to measure the effect of the subsidies on additional R&D and spillovers in a less complicated method. The same as reference model, All shocks are assumed to be normally distributed.

Assumptions are as the following:

$(a)\ \nu = (1+\rho)\varepsilon + \nu_0, (b)\ \eta \perp \varepsilon\,, (c)\eta \perp \nu_0, (d)\ \varepsilon \perp \nu_0, (\mathrm{e})\omega_j \perp \varepsilon\,, \mathrm{j} \in \{c, m\}, (\mathrm{f})\ \omega_j \perp \eta, (\mathrm{g})\ \omega_j \perp \nu_0, \mathrm{j} \in \{c, m\}, (h)\omega_c \perp \omega_m,\ (i)\eta \sim \mathrm{N}(0, \sigma_\eta^2),\ (j)\ \varepsilon \sim \mathrm{N}(0, \sigma_\varepsilon^2), (k)\nu_0 \sim \mathrm{N}(0, \sigma_{\nu_0}^2), (l)\omega_j \sim \mathrm{N}(0,1), \mathrm{j} \in \{c, m\}.$

All the parameters have been defined and determined in the section related to model discussion and econometric model.

4.4 Implication of the theoretical assumptions

The reference theoretical model is based on some assumptions. Information structure of the game model is assumed to be symmetric with incomplete information regarding the agency's type in application stage. The agency learns the project's type after grading and the firm's type is common knowledge. The agency does not have a budget constraint. However, there is a cost of financing on the agency.

109 The base model has assumed this to allow those firms with high profitability shocks to face different application cost shocks.

Spillover $V(\,)$ is proportional to R&D investment as shown in equation (6). The firm's investment is just a decision made by the firm. There is no binding contract between firm and the agency to oblige the firm to spend on R&D a specific amount according to the subsidy it receives. Moral hazard problems in the use of subsidy are assumed not to happen. There is no fixed R&D cost and constraints for firm's R&D investment which is controversial with the credit rationing assumption. As a strong assumption, this is required to reach to a comprehensive model for the whole subsidy program and at the same time it is not that important at the project level than at the firm level (Takalo et al., 2013)

The firm's specific form of profit function has been defined in a way to make it possible to derive the estimation equations. This functional form is chosen ad hoc in the reference model assuming logarithmic returns to R&D widely accepted by the literature. The functional form of the second part in profit function (equation (1)) is given by the agency's subsidy rules and has previously been used in the literature in industrial organization. The effect of the subsidy rate on the profit is assumed linear as $k = 1$ for $(1 - S_i)^k$ in equation (1). If the null hypothesis of $k = 1$ cannot be rejected then there is nonlinear effect of subsidy rate on additionality.

5. Model Estimation and discussion

Previous sections discussed how the theoretical model is linked to the empirical econometric model. Econometric model and all the specification of the equations were reviewed in the previous section. Equations (9), (10) and (12) demonstrating subsidy rate, application decision and R&D investment equations are estimated using the data described. The explanatory variables and the dependent variables involved in each estimation have been determined and previously discussed. The data and the samples have been defined in section (4) as well. In the following, the results of estimations are realized and discussed to investigate the hypotheses H.5 through H.8 framed in section 3 of chapter 2. Table (5) reports the significant results for the estimations related to subsidy rate equation, application decision equation and R&D investment equation.

5.1 Subsidy rate equation estimation

In order to estimate the subsidy rate equation (9), we first consider the evaluation method categorical variable into the estimation. The other independent variables referred to table (5) include age, size (in terms of SME), being an exporter and industry dummies. The dependent variable is the actual subsidy rates for 94 subsidized observations. As expected, the correlation matrix shows a high correlation (0.81) between evaluation method and subsidy rate (the dependent variable). In order to avoid this trouble, we run the estimations without the evaluation method categorical variables. Therefore, we exclude the evaluation method from the estimation. (appendix 4.c).

According to the reference model, coefficients can be interpreted as *marginal effects of R&D on spillovers.* The total number of observations to be applied in the estimation is 94. Age of the firm has a very slight negative effect on subsidy rates. One year of higher age reduces the subsidy rate only by 0.2%. If the relationship is linear, then everything equal, a firm 10 years younger may get 3% more subsidy rate.

Moreover, changing from base industry (manufacturing industry) to construction increases subsides rate by 18% (with a 95% confidence interval). However, the number of firms in construction sector is relatively low. The constant is also significant which may imply the effect of unobservables on the subsidy rate. Furthermore, the constant is highly significant which may show that the effect of unobservable factors and η_i on subsidy allocation play an important role. However, the effect is not so strong. This result can challenge the assumptions of previous chapter about the effect of unobservables on selection procedure. Finally the F test shows that R-squared is not zero (0.215), showing the estimation fits well.[110]

Surprisingly, being an SME or the size of the firm have no significant effects on the subsidy rate. This shows the agency does not totally allocate the subsidies based on the scheme illustrated in table (1) of chapter three. Generally, public incentive programs focus more on supporting SMEs, in comparison to less financial-restricted larger companies. However, through a part of the literature and also in the reference model, it is declared that sometimes public authorities' higher reliance and trust on larger firms' projects than SMEs due to either higher project success probability and more importantly *higher spillovers generation*, can influence on public agency's preferences in allocating incentives.

[110] We have also estimated the spillover rate equation without taking into account the industry dummies. In this new setting, beside the age remaining significant, being an exporting firm reduces the subsidy rate by 13%. This can be in contrast to the belief that the agency may allocate more funds to the firms which export outside the region and to other states.

On the other hand, SMEs own the highest share of firms in Italian economy based on size. Trento Province is of no exception. Therefore, an established large firm can send a sign of success in survival through time. This can persuade the public agency to relatively direct higher support towards larger firms as their projects will be larger and consequently *with a higher spillover effect*. Autonomous Trento Province similar to other fast developing regions, concentrating on rapid growth within the past decades, the same phenomenon can occur. All these interactions may cancel out the impact of the size of the firm.

5.2 Investment Equation Estimation

The investment equation (12), determines the effect of explanatory firms' characteristics on the marginal profitability of R&D projects. The investment amount in estimation equation stands for the planned and proposed expenditures for projects[111] and total R&D expenditures in a specific year (actual annual spending)[112]. Estimation has been carried out for both variables of actual spending and planned R&D investment, as dependent variables. The explanatory variables consist of size(in terms of log of employment), the sales-to-employee, exporting, board size and sector classification. The results in table (5) for 48 observations, show that size has a significant positive effect on actual R&D expenditure. The larger is the firm, the more she spends on annual R&D. The R-squared (0.44) is significantly high, showing the data are close enough to the fitted regression line.

After, we take the variable related to planned R&D expenditure as the dependent variable. Results for 94 observations, show that age of the firm is negatively related to the planned R&D, while size the same as actual investment equation, has a stronger positive effect. Sales/employee has a significant positive linear effect, however the effect is quite close to zero. The firms in construction sector may plan to invest less in R&D with respect to manufacturing sector. The constant is also positive significant implying unobservables may have effect on the R&D profitability. Finally, R-squared is significantly high (0.51). The detail estimated measures are shown in Appendix (4.d).

[111] Total expenditure: Spesa-Totale (In Italian)
[112] The investment dependent variable represents the amount declared in the CIS (Community Innovation Survey).

Table 5 Subsidy rate, application function and R&D investment estimation results

Variables	Subsidy Rate Equation (9)	Application decision Equation (10)	R&D Investment variable: the Planned R&D expenditures Equation (12)	R&D Investment variable: the annual R&D expenditures Equation (12)
Age	**-0.002***	0.006	**-0.027*****	-0.014
	(0.001)	(0.006)	**(0.008)**	(0.013)
Log of Employment	_	**-0.167****	**0.622*****	**0.53*****
		(0.68)	**(0.95)**	**(0.14)**
Sales/employee	-0.000	**-0.000***	**0.000****	0.000
	(0.00)	**(0.00)**	**(0.00)**	(0.00)
Exporter	-0.087	0.20	0.048	0.56
	(0.054)	(0.20)	(0.27)	(0.53)
Board Size	__	**-0.204***	-0.20	0.21
		0.124	(0.24)	(0.44)
SME	-0.058	_	_	_
	(0.055)			
Industry sector dummies	**0.185**** Δ	Significant for 3 out of 4 sectors	**-1.00**** Δ	Not Sig. for any sector._
	(0.084)		**(0.397)**	
Constant	**0.655*****	0.072	11.38	**3.009*****
	(0.048)	(0.28)	(0.41)	**(0.076)**
R-Squared	0.26	0.058 (pseudo R2)	0.51	0.44
Number of Observations	94	293	94	48

* 90% confidence level ($p<0.1$) **95% confidence level ($p<0.05$) ***99% confidence level ($p<0.001$)

Δ Significant only for construction sector.

5.3 Application Decision Estimation

A probit regression is applied to identify the effects of the firm characteristics on the application decision for 293 observations. As previously noticed, previous subsidy application variable has been put aside due to the occurrence of statistical error due to multicollinearity in probit estimation. The determining factors are age, size (in terms of log of employment), sales per employee, being exporter, board size and sector dummies. The uncentered VIFs are checked after probit estimation and there is no multicollinearity between variables and the dependent variable.

The results show that larger firms less probably apply for the subsidies. The sale-to-employee has a significant effect, however the effect is negligible. The board size has a negative effect on the probability to apply in this estimation. The bigger gets the board size of a firm, the less probable the firm applies. The results indicate that sector of activity (except for ICT) affects the application decision. Finally, the probit estimates are generated after four iterations and chi-squared is 21.62.

The previous sections have discussed the effect of firm characteristics on different stages of an R&D support program. The analysis investigates the influence of age and size of the firm, beside other explanatory factors on the mechanisms which connects R&D subsidies to R&D expenditures. It can be implied that beside the sector, age and size of the firms can influence the application, allocation (selection) and investment decisions. This can make us more reliable on the determinants applied for subsides effect evaluation in the previous chapter as well. The following section concludes the results and suggest policy implications.

6. *The effect of subsidies on additional R&D and spillover effect*

In section 2.2, it has been shown that the additional investment by being granted can be calculated as:

$$Investment\ amount\ being\ awarded\ the\ grant - investment\ withouth\ subsidies\ =$$

$$\frac{exp(X_i\beta+\varepsilon_i)}{1-s_i} - exp(X_i\beta + \varepsilon_i) = \frac{s_i}{1-s_i}\ .exp(X_i\beta + \varepsilon_i) \quad (13)$$

Referring to table (5), by applying the estimated coefficients related to covariates for investment equations, β, into additional expenditure equation, we can calculate $X_i\beta$.[113]

[113] Using predict command in stata for investment equation(s)

Consequently, as long as the predicted amount gives us $\ln[(1 - S_i)R_i]$, we can measure the predicted optimal amount of planned R&D expenditures, let us call $\overline{R_\iota}$, by estimating $\frac{exp(X_i\beta+\varepsilon_i)}{1-s_i}$. The additional amount spent for each firm referred to equation (13) is measured by $S_i\, \overline{R_\iota}$. Finally, the R&D subsidies additionality can be measures by comparing this optimal amount with the planned (and actual) R&D investment by each firm and on average for the whole population. All these calculations being carried out, the average for additional R&D expenditure is -283,626.8 (with standard deviation of 1,339,751) and less than zero, showing a crowding out effect[114]. The highest crowding out is 7,886,245 and the maximum additional investment is 3,558,113Euros.

Unlike Takalo et al. (2013), we also have the access to data on actual R&D expenditures. Therefore, we can measure the additional, substituted or crowded out expenditures comparing the estimated predicted R&D expenditure just measured with the actual amount of investment. The same as the comparison with planned R&D expenditure, the results show an average of -1,331,523 Euros have been crowded out. The results for both cases is displayed in table (6).

Table 6. The difference between the optimal R&D expenditure (predicted by model) and the planned/ realized R&D spending

	Mean	Std. dev.	Min	Max	Observations
The additional R&D expenditure (regarding planned R&D investment)	-283626.8	1,339,751	-7,886,245	3,558,113	94
The additional R&D expenditure (regarding actual R&D investment)	-1,331,523	1,413,050	-6,456,908	-95,408.49	48

[114] As a reminder, crowding out is a reduction in private investment that occurs because of an increase in government borrowing.

In order to measure the spillovers effect of subsides, we plug the estimated coefficients related to subsidy rate equation (9)[115], or in other words spillover rate equation into equation (6) in order to estimate $V(R_i(s_i), Z_i, \eta_i) = (Z_i\lambda + \eta_i)R_i$. $R_i$can be the planned or the actual amount of R&D investment. The variable V,shows how much spillover will be generated of spending R_i Euro. Hence, $(Z_i\lambda + \eta_i)$ as also shown in the section related to theoretical framework, is the spillover rate of each Euro being spent on research and development. Table (7) describes the spillover rate and spillover generated by R&D investment.

Table 7. The spillovers and spillover rate generated by subsidized firms' R&D investment

	Mean	Std. Dev.	Min	Max	Observations
Spillovers by planned investment	647,364.4	753,545.9	27794.08	4,709,812	94
Spillovers by actual investment	343,899	393,903.4	3.093893	1728.418	48
Spillover rate	0.519	0.11	0.25	0.79	94

Table (7) shows out of one euro of additional R&D investment by subsidized firms 50 Eurocents would spill over the network in the region. However, this all based on the assumption that all projects will lead to spillover effect. Moreover, on average 343,899 Euros are leaked into the network from annual R&D investment of private firms.

7. Conclusion

This chapter has estimated the equations of a modified reference structural model for public R&D incentive program using local data related to a place-based R&D grants allocation to firms in the province of Trento in Italy. The game-theoretical model structured by application decision, subsidy rate and R&D investment equations has a Nash equilibrium. The estimation of the econometric model (derived from the theoretical model) identifies the effect of different firm characteristics on participation decision of the firm, the subsidy rate decision assigned to firms'

[115] $s_i^* = 1 - g + Z_i\lambda + \eta_i$, λ :spillover rates, We assume agency's opportunity cost g=1.

projects by the local government and the planned or actual amounts spent on R&D by the firm. The estimated covariates within each equation differ according to the mechanism of subsidy allocation.

One empirical feature of this study is showing how a different context can lead to different choices on model variables and the different effects of these explanatory variables on outcome. This even shows better when the application decision equation based on the belief of the firms over the evaluation grades is simplified due to access to data on predicted R&D expenditures. Data on actual subsidy rates, R&D expenditures and firms' characteristics are provided from different data sources and merged together to shape the dataset applied for estimations. The results show how firm characteristics influence each part of the R&D subsidy program. Age and size characteristics, beside the sector in which the firms operates in, affect the decisions of both the firm and the agency sides. Moreover, The context and dataset features allow for different empirical modifications with respect to the benchmark model applied. The results determine the effect of firm (project) characteristics on all stages of the subsidization game. Size, age, exporting status, board size and sector are main factors being investigated. The results show not only there is no additional R&D expenditure, but also crowding out of subsidies occurs The base model is determined in such a format which makes it possible to evaluate the spillover effect and spillover rate of R&D spending as well. The results show that on average half (50%) of each euro spent on R&D spill overs.

Previous Chapter 3 dealt with measuring the effect of R&D subsidies on productivity controlling for firm characteristics such as size and age as control variables through different sectors. However, unobservable factors' effect and spillover effects were not presumed in the methodology used to estimate the effect. This chapter estimates the impact of characteristics on R&D application decision, subsidy allocation and R&D investment allowing for unobservables effect and spillovers. This can shed light on the black box of R&D causal effect on outcome targeted variables. Therefore, current chapter offers a complementary approach to the previous chapter estimating the place-based policy model.

Finally, the structural model estimation can be compared with the ex-post treatment analysis, evaluating the R&D policy after the implementation. The evaluation of direct impact of R&D subsidies on target variables such as total factor productivity (chapter 3) combined with modelling the R&D policy (chapter 4), may provide policy makers (at local, regional and national levels) insights about the future policy designs or policy modifications. Application of new model specifications related to other different institutional contexts, relaxing some theoretical assumptions and finally use of other datasets at regional (local) and national levels, allow for a comparative policy estimation which can be an interesting topic for future studies.

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Appendices:

Appendix 1.a

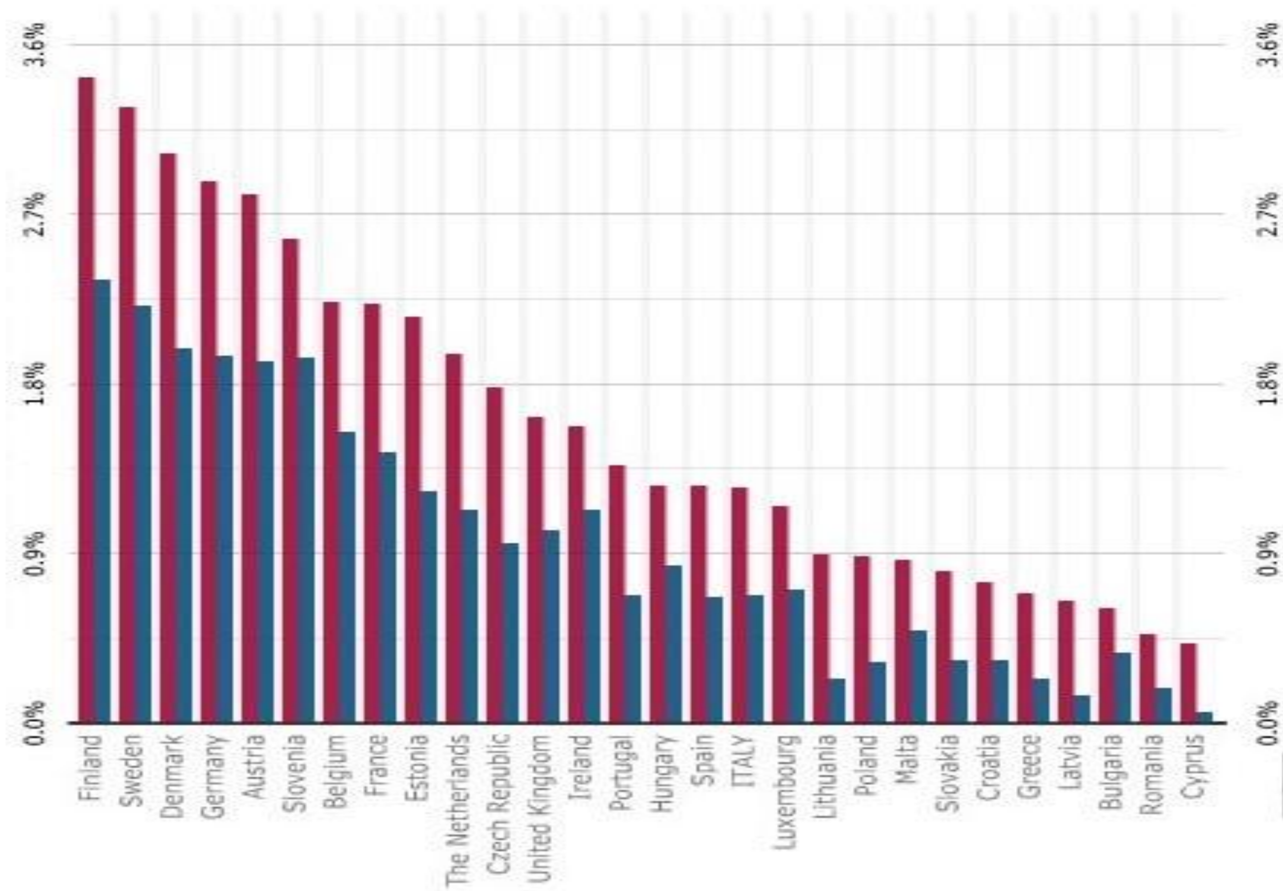


Figure 1.a.1 Total R&D Expenditure to GDP (GERD/GDP) and Business R&D Expenditure to GDP (BERD/GDP) at EU national level in 2012

Source: Elaboration to ISTAT report based on The European system of national and regional accounts (ESA 2010)

Figure (1.a.1) shows the amount of gross national R&D expenditures to GDP at national level for year 2012. R&D expenditure in the EU-28 countries accounted for 2.01% of the EU GDP. Figure identifies the total national R&D intensity as one of the key factors of Europe 2020 strategy in the forms of expenditure[116](GERD) and business (private) R&D expenditure[117] (BERD) within the European context.

Finland (3.43%), Sweden (3.28%) and Denmark (3.03%) were the only countries performed above the 3 percent ratio. These were followed by Germany (2.88%) and Austria (2.81%), and well above France (2.23%), the Netherlands (1.81%) and the United Kingdom (1.63%). As one of the largest economies in the EU, Italy (1.26%)118 is performing less than Portugal (1.37%), Hungary (1.38%) and Spain (1.27%). The R&D intensity (the ratio of GERD to GDP) increased from 1.31% in 2013 to 1.38% in 2014. Italy's 2020 target of 1.53% is not out of reach; however, the country still should spend on R&D to achieve the 3% target of the 2020 strategy, currently matched only by Scandinavian economies. (Sources: Italian National Institute of Statistics [ISTAT119] report on scientific research and Eurostat report on research and development statistics).

[116] The gross domestic expenditure on R&D (GERD)
[117] Business enterprise expenditure on *R&D (BERD)*
[118] With an increase of 0.05 percent compared to 2011.
[119] ISTAT (In Italian: Istituto nazionale di statistica) is a public research organization founded in 1926 as the main producer of official statistics at the service of citizens and policy-makers. ISTAT has been performing the role of directing, coordinating, and providing technical assistance and training within the National Statistical System (Sistan) since 1989.

Appendix 1.b Share of innovative enterprises[120] in total number of enterprises at national and regional level

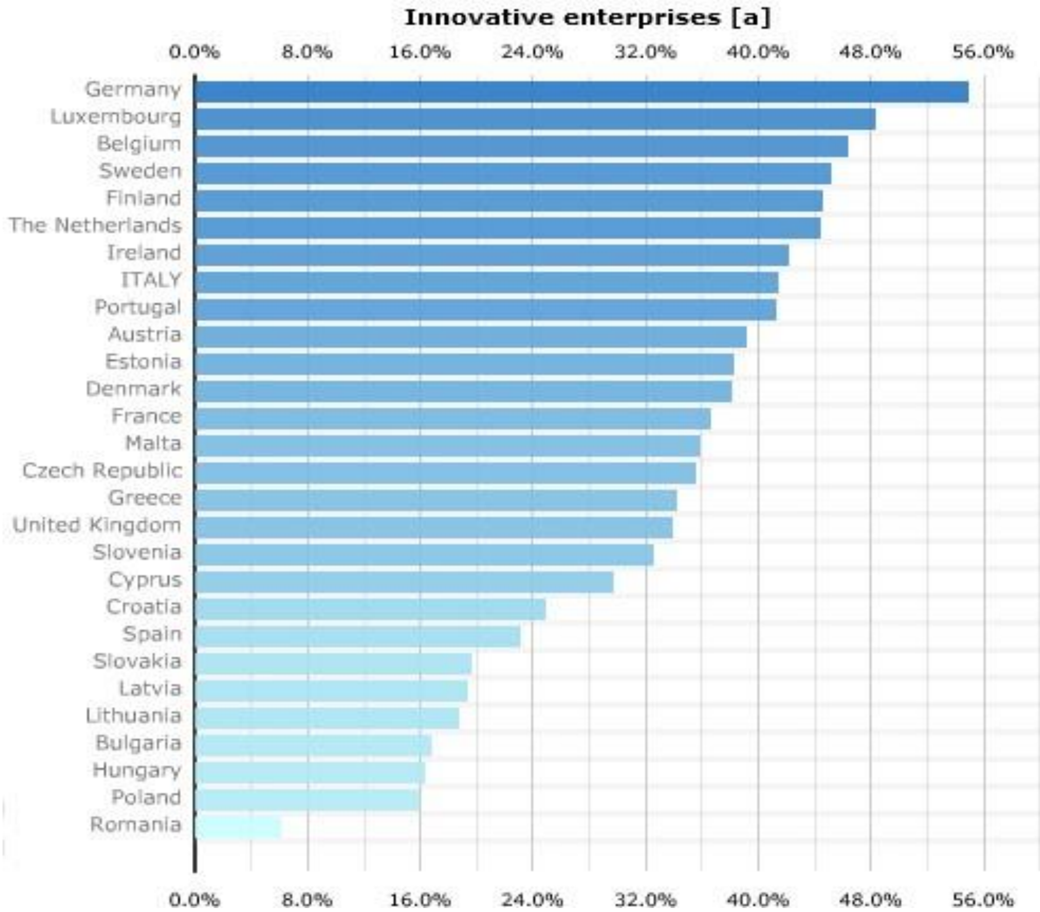


Figure 1.b.1 Share of innovative enterprises for EU countries in 2012

Source: EU Community Innovation Survey (CIS)

The percentage of Italian innovative enterprises in 2010-2012 period, was above the European average (41.5 percent versus 36.0 percent). Figure (1.b.1) illustrates the share of innovative enterprises in Europe. Many northern countries like Sweden, Finland and the Netherlands follow Germany with a 55% share at the top of the list. Ireland (42.3%), Italy, Portugal (41.3%) and Estonia (38.4%), being above the European average had more innovative firms than

[120] An innovative firm is one that has implemented an innovation during the period under review according to Oslo manual.

France (36.7%) and UK (34.0%). Eastern Europe and Spain had a low propensity for innovative enterprises compared to the average.

The number and percentage of innovative enterprises in Italy increased from 31.5% to 35.5% (above the European average) between 2010 to 2012. Figure (1.b.1) shows Italy in 2012, has a high percentage of innovative enterprises mostly SMEs (more than 40% of enterprises do innovation) in Europe. Innovation activity was mostly focused in large industrial enterprises with a value of 45.4% in comparison to 29.5% in service sector and 20.3% in the construction sector (ISTAT report on Innovation in Italian enterprises, December 2014).

At regional level, the northern regions represent the majority of innovative enterprises. In 2010 to 2012 period, the most innovative region has been Veneto (43.5%), followed by Friuli-Venezia Giulia (41.1%), Piedmont (39.2%) and Lombardy (39.1%). Figure (1.b.2), illustrates the number of innovative enterprises for different regions in Italy.

The noticeable fact here is the significant difference of Veneto region in different rankings based on total R&D expenditures and innovative enterprises ratios for this period. For instead, in the period of 2010 to 2012, Veneto with an amount just slightly higher than 1% for total R&D expenditure to GDP and an amount around 0.7% for private R&D expenditure to GDP; stands just in the middle of the ranking table, while at the same time span, the region has the highest ratio for innovative firms to total number of enterprises. One explanation can be, although there are many innovative enterprises, however those entities invest smaller amount for their R&D projects in comparison to their counterparts in other regions like Emilia-Romagna or Trento. Friuli-Venezia Giulia and Toscana, follow the same story but less striking. Not surprisingly, Lazio does not posit in top of the list for innovative enterprises ratio, but it performs as one of the best in respect to total R&D expenditures ratio, most probably because the state invest significant larger amounts in R&D compared to private enterprises in the region.

The lowest values happen for Molise (20.1%), Valle d’Aosta (22.3%) and Calabria (23.8%). Puglia (30.4%) and Basilicata (28.3%) represent the highest measures for R&D enterprises intensity among southern regions. Based on the ISTAT report, enterprises in the north regions tend to adopt different types of innovations, while firms in the center except Toscana, do not take this combined approach.

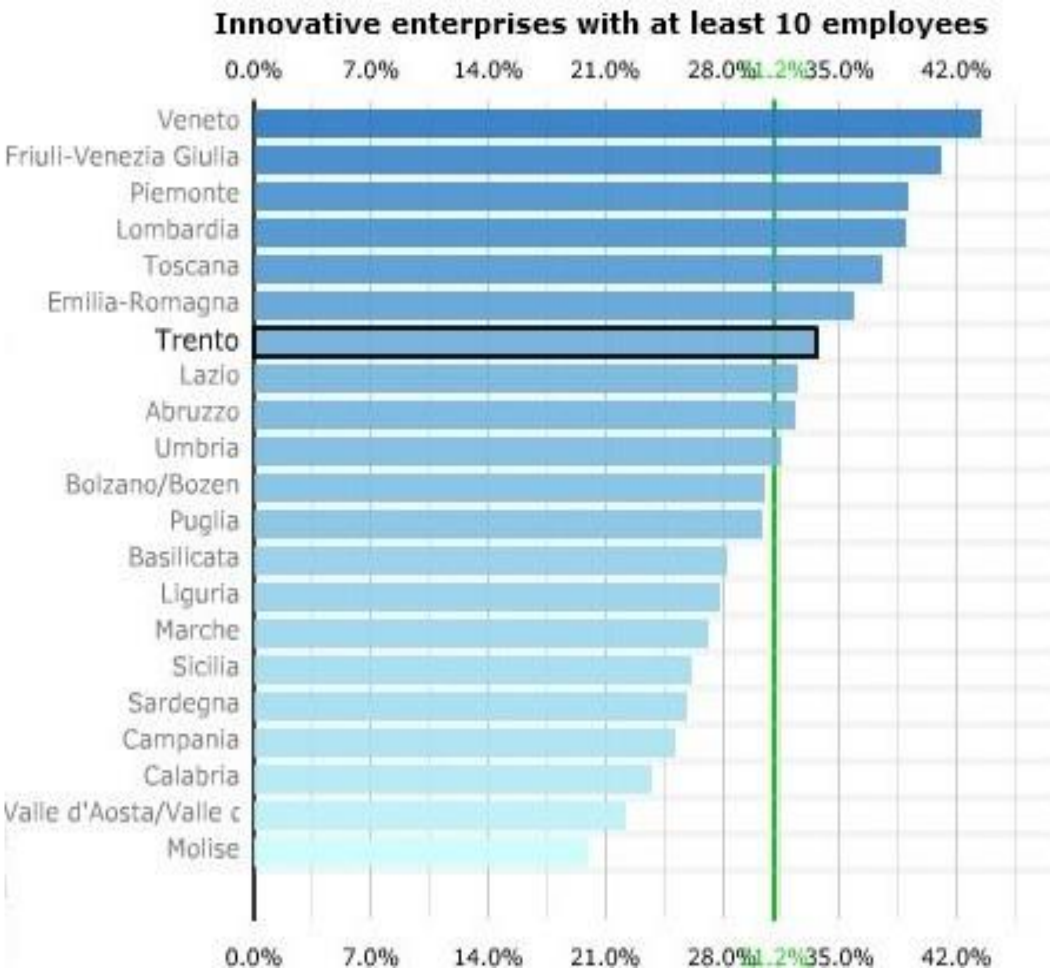


Figure 1.b.2 The share of innovative enterprises with less than 10 employees for regions in Italy, 2010-2012

Innovative enterprises in Trento has a share of 33.7% of total enterprises (with more than 10 employees), slightly higher than the Italian average (31.2%). According that the autonomous province of Trento has one of the highest total R&D expenditure ratio in comparison with other regions, it is implied that public agency (the province) has significantly invested in R&D. The regulations for R&D stimulation enacted in 1999 in the province and the agency Trento province has introduced due to reach this aim in 2009, confirm the desire of the province for higher public or private R&D investment.

Appendix 3.a

Model (1) formulates the basic model primarily proposed by CCR in 1978 as the following:

$$\text{Max } h_0 = \frac{\sum_{r=1}^{t} u_r y_{rj_0}}{\sum_{i=1}^{m} v_i x_{ij_0}}$$

subject to

$$\frac{\sum_{r=1}^{t} u_r y_{rj}}{\sum_{i=1}^{m} v_i x_{ij}} \le 1, \quad j = 1, \ldots, n,$$

$$u_r,\ v_i \ge \varepsilon, \quad \forall r \text{ and } i,$$

where

y_{rj} = amount of output r from unit j,

x_{ij} = amount of input i to unit j,

u_r = the weight given to output r,

v_i = the weight given to input i,

n = the number of units,

Model (1)

The solution of this model demonstrates the maximum relative efficiency related to unit j_0, subject to the fact that the efficiency of all other units is restricted to be below 1 (100%). This is more like a system approach and engineering perspective towards a decision making unit in specific a firm, which the efficiency of the system is bounded between zero and one. The interesting feature of this model is that variables u_r and v_i which are the relative weights for outputs and inputs respectively are unknown and will be realized by putting information about the quantity of inputs and outputs for each DMU for n different objective functions with the same restrictions. Variables u_r and v_i are actually the unknown parameters to be measured flexibly by solving the CCR model.

Model (1) is a fractional linear model which cannot be solved using standard linear programming (LP) methods; hence a trick to set the denominator of the equation equal to

1(100%)[121] and adding the same assumption to the restrictions the model is subjected to, will turn model (1) to a linear programming model as formulated in model (2).

$$\text{Max } h_0 = \sum_{r=1}^{t} u_r y_{rj0}$$

subject to

$$\sum_{i=1}^{m} v_i x_{ij0} = 100,$$

$$\sum_{r=1}^{t} u_r y_{rj} - \sum_{i=1}^{m} v_i x_{ij} \leq 0, \quad j = 1, \ldots, n,$$

$$-u_r \leq -\varepsilon, \quad r = 1, \ldots, t,$$

$$-v_i \leq -\varepsilon, \quad i = 1, \ldots, m.$$

Model (2)

Model (2) must be separately solved for each unit which means to generate the relative efficiency measures for all the units; a mathematical optimization problem in '*primary form'* with $t + m$ variables and $n + t + m + 1$ constraints must be solved. Although the constrains are all the same in each turn of solution, however in practice because the number of units n is large the computation problem takes more memory and time. One can benefit from duality theorem in LP due to optimize the computation efficiency.

As long as the constraints are the same in each turn of calculation and the 'dual form' of the primary model (model M2) will have $m + t$ constraints which is way less than primary form's $n + t + m + 1$ constraints in application. For example if the number of units are 20 and the model has three inputs and one output then solution to primary problem takes into account 25 constraints, while solution to dual problem demands consideration of only 4 constraints. Consequently, computation of the dual form is more efficient. The dual form of model (2) will be formulated as the following:

[121] This modification is possible because in maximization of a ratio the important thing is to maximize the relative magnitudes of numerator to denominator while the actual values of them do not count. Therefore, it is possible to set the denominator constant to any fixed value (arbitrarily and preferably 1 or 100) and optimize the numerator.

$$\text{Min} \quad 100 Z_0 - \varepsilon \sum_{r=1}^{t} s_r^+ - \varepsilon \sum_{i=1}^{m} s_i^-$$

subject to

$$x_{i j_0} Z_0 - s_i^- - \sum_{j=1}^{n} x_{ij} \lambda_j = 0, \quad i = 1, \ldots, m,$$

$$-s_r^+ + \sum_{j=1}^{n} y_{rj} \lambda_j = y_{r j_0} \quad r = 1, \ldots, t,$$

$$\lambda_j, s_i^-, s_r^+ \geq 0 \quad \forall j, r \text{ and } i,$$

$$Z_0 \text{ unconstrained.}$$

Model (3)

It is not only computational convenience that makes the dual form interesting. Values of λ_js are used to construct a composite unit outperforming counterpart unit j_0. The unit j_0 is efficient if slacks $s_i^- and\ s_r^+$ are zero and Z_o is equal to one. However, if unit j_0 is inefficient then Z_o is lower than one and/or slacks are positive. This model is known as BCC (1984) model which is capable to measure the variable return to scale as well.

Appendix 3.b Dataset Construction Procedures

Due to construction of the dataset used in this essay, The APIAE and AIDA datasets will be partially merged together with other datasets provided by ISPAT. These datasets include PITAGORA dataset and dataset related to CIS (Community Innovation Survey). PITAGORA provides balance sheet data and CIS dataset (RS dataset) covers information about R&D activity by firms in Trento.Table (3.b.1) shows number of R&D subsidizations for each year. The data for R&D subsidies are available from 2001 up to 2013. It describes the number of firm-year observations where the complete data for different consecutive years (from two to seven years) in order to measure the Malmquist Productivity Index is available. Year 2007 has been dropped out because the data for tangible fixed asset as an input in year 2007 is used in order to calculate moving average tangible fixed asset for the year 2008 due to measure the frontier.

Table 3.b.1 Treatment frequency by year from 2001 to 2013 and the total number of observations including observations with missing values from 2007 to 2014

YEAR	NUMBER OF TOTAL OBS. IN AIDA DATASET USED FOR PRODUCTIVITY MEASUREMENT	NUMBER OF R&D SUBSIDIES (TREATMENTS)
2001	_	*1*
2002	_	*4*
2003	_	*18*
2004	_	*38*
2005	_	*41*
2006	_	*24*
2007	*5484*	*38*
2008	*5485*	*38*
2009	*5478*	*47*
2010	*5466*	*69*
2011	*5453*	*89*
2012	*5419*	*153*
2013	*5488*	*40*
2014	*5506*	_
TOTAL	_	***600***

The occurrence of the consecutive years can obtain different scheme; for example for 4 years of consecutive data, we can have the years between 2009_2013 or 2011_2014 or other possible combinations of years. Interestingly, there are 831 observations with 7 year of consecutive data availability which is the main pattern for measuring the impact of R&D subsidy program of total factor productivity. However, in case of treatment measurement for a pre and post treatment effect we have to notice the fact that the observations without consecutive data can also be considered into analysis. For instant, if a firm is treated in 2010 and we have the data required to measure Malmquist Index (efficiency or technical change) between 2009 and 2011 then the observation can remain in the analysis. Malmquist Index is measured only using observations without any missing values for inputs-output variables.

The number of observations (firm-year) for different previous treatment received is pointed out in table (3.b.2). 43,189 out of 44379 observations have not been treated at any point for the period between 2001 to 2013. A pattern of the subsidies allocation over time has been provided for an example of enterprises in appendix. Each enterprise is labeled with a unique fiscal code.

Table 3.b.2 Distribution of number of previous subsidies received for all firm-year observations

NUMBER OF PREVIOUS R&D SUBSIDIES (TREATMENT) RECEIVED BY AN ENTERPRISE IN A SPECIFIC YEAR	NUMBER OF OBSERVATIONS
0	*43,189*
1	*580*
2	*297*
3	*164*
4	*64*
5	*31*
6	*19*
7	*12*
8	*11*
9	*6*
10	***6***

Measuring the Malmquist Index, observations with consecutive years of available information on inputs and outputs are required due to capture the change. As previously noted, the data used for MPI calculation relates to the years after 2008. Hence, the maximum number of possible years for the analysis will be seven years while the minimum years of available data is of course two years. Moreover, the user-written STATA code to measure the MPI has the feature which generates the efficiency results only for observations with the same exact numbers of years for data available. In other words, the requirement to compile the data is to build *a balanced panel dataset*.

Table (3.b.3) traces the frequency of exact consecutive years for available Malmquist measures as the output target variables. Availability of an exact period of four consecutive years represents the highest number of firms (947), followed by a period of consecutive seven years for 831 firms. The next frequency represents firms obtaining only exact 2 years of consecutive data with 595 firms. Trading off to obtain the highest number of observations; forming a balanced panel dataset with observations including firms with seven consecutive years of input/output information will be the best option.[122]

Table 3.b.3 Number of maximum consequences of years for enterprises (starting 2008 to 2014) to form the balanced dataset

NUMBER OF MAXIMUM CONSEQUENCES OF YEARS FOR OBSERVATIONS (STARTING 2008 TO 2014)	FREQUENCY OF ENTERPRISES
2	*595*
3	*276*
4	*947*
5	*177*
7	*831*

Finally, the primary balanced panel dataset to measure MPI measures provides information on inputs (number of employees, moving-average tangible asset as the proxy for capital and the intermediate inputs) and output(Total revenue), leading to calculation of total factor productivity components. After generating the measures for total factor productivity, the panel data will be

[122] At the same time $7 \times 831 = 5817$ represent the highest number of observations in comparison with all other settings.

merged with the dataset related to the R&D subsidies. Obviously, the subsidies happening before 2008 will be dropped as the productivity measures dates after 2008. Subsequently, the new panel dataset has the information on treatment in binary format and the total factor productivity measures, together with variables representing the covariates due to carry out PSM method.

Excel table (3.b.4) covers a snapshot of the balanced panel dataset formed and constructed by a complex long data cleaning, merging and coding processes. First column denotes the firm as the decision making unit (DMU). After data cleaning, polishing and restructuring there remain 4151 observations (firm-year), i.e. longitudinal data for 593 enterprises within 7 years (from 2008 to 2014). INP1, INP2 and INP3 represent inputs as number of employees, capital proxy and intermediate inputs. The scale for INP2 and INP3 are thousand Euros. DEA method is not scale sensitive to the dimension, hence scale of inputs or outputs do not matter as long as they change by the same proportion. OUT1 is the total revenue in thousand Euros to be used as the output for MPI model. Applying inputs/output quantities in Malmquist model using CRS output-orientated DEA; the total factor productivity change and all components of the Malmquist Index will be generated.

These measures will be lagged to investigate the short-term and long term effect of the R&D subsidy program. Malmquist Index captures the change of distance measures, therefore there will not be any measure for year 2008, as we do not possess the information for one input (moving-average-fixed-asset) in 2007. Thus, the efficiency measures are related to a period of 6 years from 2009 to 2014. This allows to check a maximum lag of 5 years (5 different lags) for each index. All the indices defining total factor productivity change have been explained in the main text.

Control variables as mentioned previously, are size, age and the sector which enterprise operates. To measure the impact of R&D subsidy, control variables (the independent variables for selection) size and age are lagged one year due to control the delay of their effect on treatment decision. Sector (industry) counts for another control observables to be controlled in PSM method.

The balanced panel dataset constructed and used in this study include many other variables which can be used for further investigations or different setting up of the models beside robust checks. One variable used is production price index (PPI) which can be used to deflate the production factors mainly revenue. PPI index has been merged from the dataset provided by ISTAT. The base year for the index is 2010. The dataset provides information on various other variables like denomination of the firm (company name), number of recorded subsidiaries, SIC industry code, mergers or acquisitions, number of directors in the board, number of companies in corporate group, total inventory and profit and loss measure. In addition, it consists of detailed data on R&D subsidies.

Table 3.b.4 Excel sheet: A brief illustration of the final balanced panel dataset used for policy impact evaluation

DMU	Year	R&D Sub	INP1	INP2	INP3	OUT1	tfpch	effch	techch	pech	sech	All TFP measures lagged for 5-4-3-2-1 years
1	2008	0	26	462.49	2886.317	3769.669	.	.	.	.	.	
1	2009	0	26	627.88	2899.445	3804.715	1.0012	0.96554	1.036945	1.06459	0.907	
1	2010	0	25	1074	3015.055	3940.154	1.0288	1.09388	0.940543	1.04683	1.0449	
1	2011	1	27	1285.9	3103.736	4042.052	1.009	0.88893	1.135111	1.02305	0.8689	
1	2012	0	28	1127.1	3283.907	4236.737	0.9651	0.90968	1.060889	0.96684	0.9409	
1	2013	0	25	1042.5	3284.503	4188.073	1.0068	0.99881	1.007998	1.05638	0.9455	
1	2014	0	25	994.27	3129.209	3993.477	1.0084	1.15848	0.870468	0.99553	1.1637	
j	2008	0	x1	r1	f1	k1	.	.	.	.	.	
j	2009	0	x2	r2	f2	k2	t2	a2	c2	p2	h2	
j	2010	0	x3	r3	f3	k3	t3	a3	c3	p3	h3	
j	2011	1	x4	r4	f4	k4	t4	a4	c4	p4	h4	
j	2012	0	x5	r5	f5	k5	t5	a5	c5	p5	h5	
j	2013	0	x6	r6	f6	k6	t6	a6	c6	p6	h6	
j	2014	0	x7	r7	f7	k7	t7	a7	c7	p7	h7	
n	2008	0	y1	s1	g1	l1	.	.	.	.	.	
n	2009	0	y2	s2	g2	l2	u2	b2	d1	q2	i2	
n	2010	0	y3	s3	g3	l3	u3	b3	d2	q3	i3	
n	2011	1	y4	s4	g4	l4	u4	b4	d3	q4	i4	
n	2012	1	y5	s5	g5	l5	u5	b5	d4	q5	i5	
n	2013	0	y6	s6	g6	l6	u6	b6	d5	q6	i6	
n	2014	0	y7	s7	g7	l7	u7	b7	d6	q7	i7	

DMU	Year	CNTROL1:Size	Size-lagged	CONTROL2:Age	Age-lagged	Industry Code:ATECO2007	3-2-1 digit Industry Code	Industry Dummies	Production Price Index
1	2008	26	26	88	89	471140	471,47,4	Wholesale and retail D	100.6069
1	2009	26	25	89	90	471140	471,47,4	Wholesale and retail D	100.2478
1	2010	25	27	90	91	471140	471,47,4	Wholesale and retail D	100.0081
1	2011	27	28	91	92	471140	471,47,4	Wholesale and retail D	101.5068
1	2012	28	25	92	93	471140	471,47,4	Wholesale and retail D	102.5249
1	2013	25	25	93	94	471140	471,47,4	Wholesale and retail D	102.8415
1	2014	25	.	94	.	471140	471,47,4	Wholesale and retail D	103.3912
j	2008	x1	x2	w1	w2	631110	631,63,6	ICT D	p1
j	2009	x2	x3	w2	w3	631110	631,63,6	ICT D	p2
j	2010	x3	x4	w3	w4	631110	631,63,6	ICT D	p3
j	2011	x4	x5	w4	w5	631110	631,63,6	ICT D	p4
j	2012	x5	x6	w5	w6	631110	631,63,6	ICT D	p5
j	2013	x6	x7	w6	w7	631110	631,63,6	ICT D	p6
j	2014	x7	.	w7	.	631110	631,63,6	ICT D	p7
n	2008	y1	y2	z1	z2	310930	310,31,3	Manufacturing D	o1
n	2009	y2	y3	z2	z3	310930	310,31,3	Manufacturing D	o2
n	2010	y3	y4	z3	z4	310930	310,31,3	Manufacturing D	o3
n	2011	y4	y5	z4	z5	310930	310,31,3	Manufacturing D	o4
n	2012	y5	y6	z5	z6	310930	310,31,3	Manufacturing D	o5
n	2013	y6	y7	z6	z7	310930	310,31,3	Manufacturing D	o6
n	2014	y7		z7	.	310930	310,31,3	Manufacturing D	o7

Appendix 3.c

Data and variables related to enterprises active in the region

The data on entities in the province comes from Aida[123] dataset which is the Bureau van Dijk's product on company information for Italy. Aida covers firm-level data about one million companies. In this study, the basic primary dataset extracted from the Aida database includes information for 5,506 enterprises operating in Trento province for 7 years from 2007 to 2014. This shapes a balanced dataset with 44,048 observations at firm-year level. Not surprisingly, the dataset contains missing values for different variables in which we are interested to carry out our analysis. However, it will be polished and cleaned before running the related analysis. In the following, some characteristics and measures in the AIDA dataset related to next chapters' analysis will be statistically described in table (3.c.1). As long as the majority of entities are SMEs, the mean size of the enterprise in Trento is about 14 employees for 33,697 firm-year observations, while the maximum size reaches high to 5,342 employees. The oldest firm ages 211 years old established in 1806, while the average age is 20 years. Other specific information related to balance sheet data can be followed in the table. Data on the location which the headquarter of the enterprise has been registered can be found

Table 3.c.1 Descriptive statistics for enterprises active in Trento Province (2007-2014)

Variable	Number of Obs.	Mean	Std. Dev.	Min	Max
Number of Employees	*33,697*	*13.98448*	*76.21374*	*0*	*5,342*
Foundation year	*44,048*	*1996.938*	*17.58255*	*1806*	*2014*
Age (in 2017)	*44,048*	*20.0623*	*17.58255*	*3*	*211*
Number of directors	*44,048*	*3.4753*	*4.395775*	*0*	*68*
Number of companies in corporate groups	*44,048*	*4.395775*	*85.46729*	*0*	*1,906*
Number of recorded subsidiaries	*44,048*	*0.7962223*	*2.247087*	*0*	*58*
Total Assets*	*36,404*	*5,967.093*	*36,087.25*	*0*	*1,460,016*
Total Inventory*	*36,402*	*916.1578*	*4,807.495*	*0*	*365,472.6*
Total Revenue*	*36,256*	*3,653.745*	*21,309.81*	*0*	*805,935.5*
Total R&D Expenditure*	*20,069*	*11.59474*	*173.4992*	*0*	*10,175.78*

* In Thousand Euros

[123] Italian company information and business intelligence: In Italian (Analisi Informatizzata delle Aziende Italiane)

Appendix 3.d: Sector classification using ATECO2007 categorization

ATECO 2007 has been reinforced since 1 January 2008, replacing the previous ATECO 2002 which was an update of the ATECO 1991 in 2002. The classification of economic activities (ATECO) is a type of classification adopted by the Italian National Institute of Statistics (ISTAT). It is the Italian translation of the Nomenclature of Economic Activities (NACE) created by Eurostat while being adopted to the Italian economic system. This classification represents the national version of the European coding system called Nace Rev. 2.[124] ATECO 2007 categorization has been approved and enforced by other institutional figures like related ministries, the bodies in charge of managing main administrative data sources on enterprises (the Revenue Agency, Chambers of Commerce, social security institutions, etc.) and the main business associations.

Classification of observations into groups by Industry Codes

Table (3.d.1) shows a classification of industries based on first digit of sector code. The first column defines the first digit of the industry ATECO2007 code, while the second and third columns represents the sectors covered by this first digit. There are overlaps between the sectors with different activities in our analysis; for instant, our analysis on the categorized data for all firms with the first ATECO2007 number of 3 does not include only one specific sector, say manufacturing. The firms with number 3 as their first digit for ATECO2007 code are classified within three different industries; first manufacturing; second, electricity, gas, steam and air conditioning; and third, water supply, sewerage, waste management and rehabilitation. The same holds for industries and services starting with digits 4,5,6 and 7. The impact evaluation will be carried out using stratifying based on first digit of ATECO code. However, as a result of overlap between sectors discussed, this categorization of firms leads to a non-homogenous distribution of firms under analysis. Therefore, it is essentially required to categorize enterprises independent of the first sector code digit. Thus, firms are classified based on the exact industry and sector they belong to (Table (3.d.2)). That is noteworthily to say industries under analysis are only those that an R&D subsidy allocation has occurred at least once within the period of study[125].

[124] published in the Official Journal of 20 December 2006 (Regulation (EC) no 1893/2006 of the European Parliament and of the Council of 20 December 2006).
[125] This excludes industries and services with letter codes A,B, and O through U

Table 3.d.1 . The sector classification of the dataset used for treatment effect analysis

ATECO2007 Sector Code (First Digit)	*Industry or Service*	*Code in ATECO2007 Classification*
1	*MANUFACTURING*	*C*
2	*MANUFACTURING*	*C*
3	*MANUFACTURING (Up to two digit code 35)* *ELECTRICITY, GAS, STEAM AND AIR CONDITIONING (two digit codes between 35 to 36)* *WATER SUPPLY; SEWERAGE, WASTE MANAGEMENT AND REHABILITATION (two digit codes between 36 to 40)*	*C,D,E*
4	*CONSTRUCTION (41 to 45)* *WHOLESALE AND RETAIL TRADE; REPAIR OF MOTOR VEHICLES AND MOTORCYCLES (45 to 49)* *TRANSPORTATION AND STORAGE (49 to 54)*	*F,G,H*
5	*TRANSPORTATION AND STORAGE (49 to 54)* *ACTIVITIES OF ACCOMMODATION AND FOOD SERVICE (55 to 58)* *INFORMATION AND COMMUNICATION (58 to 64)*	
6	*INFORMATION AND COMMUNICATION (58 to 64)* *FINANCIAL AND INSURANCE (64 to 68)* *REAL ESTATE (68 to 69)* *PROFESSIONAL, SCIENTIFIC AND TECHNICAL ACTIVITY (69 to 75)*	*J,K,L,M*

7	PROFESSIONAL, SCIENTIFIC AND TECHNICAL ACTIVITY (69 to 75) HIRE, TRAVEL AGENCIES, SUPPORT SERVICES FOR BUSINESSES (77 to 82)	M,N

Table 3.d.2 . Classification of industries and sectors based on first letter code in ATECO2007 and their range in two-digit level of aggregation code

Sector (Industry or Service)	Classification Letter Code in ATECO2007	Start and End of Two Digit Range in ATECO2007
MANUFACTURING	*C*	*10_34*
ELECTRICITY, GAS, STEAM AND AIR CONDITIONING	*D*	*35_36*
WATER SUPPLY; SEWERAGE, WASTE MANAGEMENT AND REHABILITATION	*E*	*36_40*
CONSTRUCTION	*F*	*41_45*
WHOLESALE AND RETAIL TRADE; REPAIR OF MOTOR VEHICLES AND MOTORCYCLES	*G*	*45_49*
TRANSPORTATION AND STORAGE	*H*	*49_54*
ACTIVITIES OF ACCOMMODATION AND FOOD SERVICE	*I*	*55_58*
INFORMATION AND COMMUNICATION	*J*	*58_64*
FINANCIAL AND INSURANCE	*K*	*64_68*
REAL ESTATE	*L*	*68_69*
PROFESSIONAL, SCIENTIFIC AND TECHNICAL ACTIVITY	*M*	*69_75*
HIRE, TRAVEL AGENCIES, SUPPORT SERVICES FOR BUSINESSES	*N*	*77_82*

Elaboration on ISTAT Industry Categorization Database

Appendix 3.e

balancing satisfaction

Manufacturing:

pscore treatment Employees_lagged age_lagged, pscore(myscore_manufacturing)

```
******************************************************
Step 1: Identification of the optimal number of blocks
Use option detail if you want more detailed output
******************************************************


The final number of blocks is 5

This number of blocks ensures that the mean propensity score
is not different for treated and controls in each blocks



**********************************************************
Step 2: Test of balancing property of the propensity score
Use option detail if you want more detailed output
**********************************************************


The balancing property is satisfied


This table shows the inferior bound, the number of treated
and the number of controls for each block
```

Inferior of block of pscore	treatment 0	1	Total
.031282	605	19	624
.05	372	31	403
.1	52	12	64
.2	5	1	6
.4	2	2	4
Total	1,036	65	1,101

```
Note: the common support option has been selected


*******************************************
End of the algorithm to estimate the pscore
*******************************************
```

-> treatment = 0

Variable	Obs	Mean	Std. Dev.	Min	Max
pscores_ma~g	1,063	.0554998	.0424459	.0299227	.7096618

-> treatment = 1

Variable	Obs	Mean	Std. Dev.	Min	Max
pscores_ma~g	65	.087386	.0923018	.031282	.5720045

```
. bysort treatment: sum myscore_manufacturing
```

-> treatment = 0

Variable	Obs	Mean	Std. Dev.	Min	Max
myscore_ma~g	1,063	.0554998	.0424459	.0299227	.7096618

-> treatment = 1

Variable	Obs	Mean	Std. Dev.	Min	Max
myscore_ma~g	65	.087386	.0923018	.031282	.5720045

Appendix 3.f

balancing satisfaction

ICT

```
. table treatment
```

treatment	Freq.
0	341
1	23

```
. pscore treatment Employees_lagged , pscore(pscores2_ICT)
```

```
****************************************************
Algorithm to estimate the propensity score
****************************************************
```

```
The treatment is treatment
```

treatment	Freq.	Percent	Cum.
0	341	93.68	93.68
1	23	6.32	100.00
Total	364	100.00	

```
Estimation of the propensity score

Iteration 0:   log likelihood = -76.944953
Iteration 1:   log likelihood = -71.466943
Iteration 2:   log likelihood = -71.236798
Iteration 3:   log likelihood = -71.236778

Probit regression                               Number of obs   =        312
                                                LR chi2(1)      =      11.42
                                                Prob > chi2     =     0.0007
Log likelihood = -71.236778                     Pseudo R2       =     0.0742
```

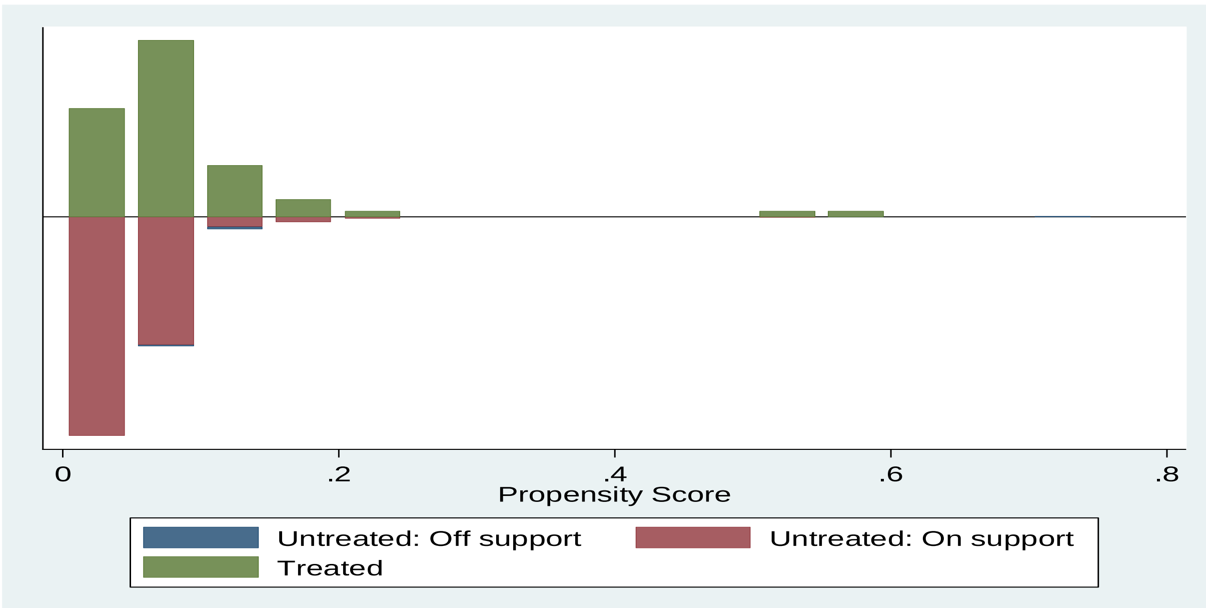
treatment	Coef.	Std. Err.	z	P>|z|	[95% Conf.	Interval]
Employees_~d	.0030261	.0008741	3.46	0.001	.0013128	.0047394
_cons	-1.68713	.1291632	-13.06	0.000	-1.940285	-1.433975

```
******************************************************
Step 1: Identification of the optimal number of blocks
Use option detail if you want more detailed output
******************************************************


The final number of blocks is 5

This number of blocks ensures that the mean propensity score
is not different for treated and controls in each blocks



**********************************************************
Step 2: Test of balancing property of the propensity score
Use option detail if you want more detailed output
**********************************************************


The balancing property is satisfied


This table shows the inferior bound, the number of treated
and the number of controls for each block

  Inferior |
  of block |       treatment
of pscore  |         0          1 |     Total
-----------+----------------------+----------
         0 |       336         20 |       356
        .2 |         4          0 |         4
        .3 |         0          2 |         2
        .4 |         0          1 |         1
        .6 |         1          0 |         1
-----------+----------------------+----------
     Total |       341         23 |       364


*******************************************
End of the algorithm to estimate the pscore
*******************************************

. bysort treatment: sum pscores2_ICT

------------------------------------------------------------------------------------------------------------
-> treatment = 0

    Variable |        Obs        Mean    Std. Dev.       Min        Max
-------------+---------------------------------------------------------
pscores2_ICT |        291    .0626038    .0544322   .0460808   .7917204

------------------------------------------------------------------------------------------------------------
-> treatment = 1

    Variable |        Obs        Mean    Std. Dev.       Min        Max
-------------+---------------------------------------------------------
pscores2_ICT |         21    .1221762    .1379745   .0472622   .5654595
```

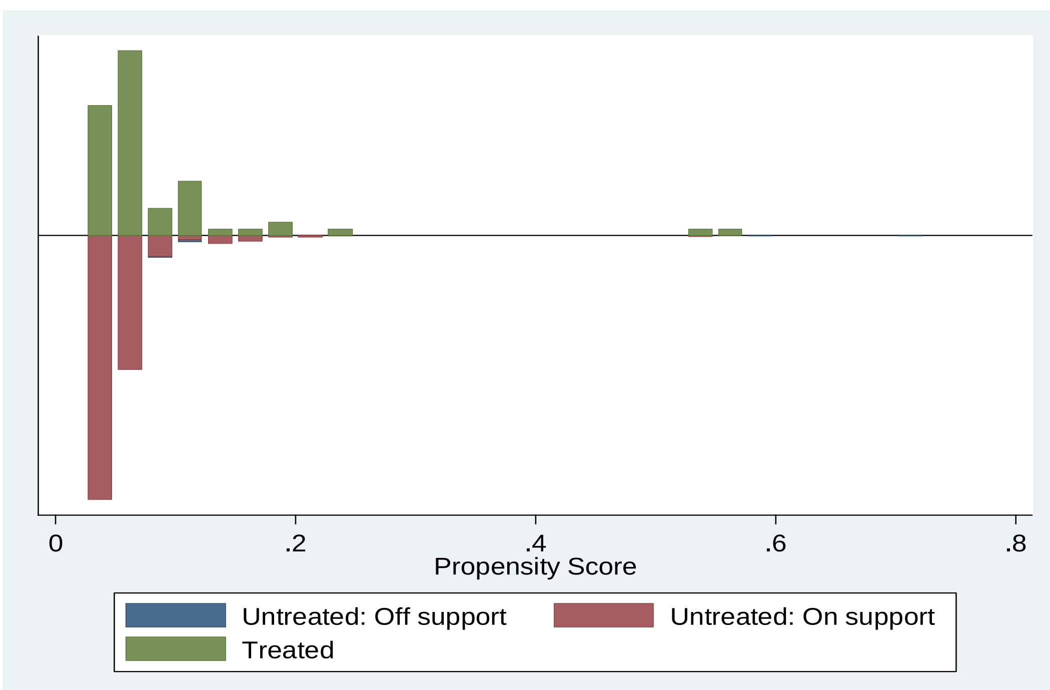
Appendix 3.g

Manufacturing

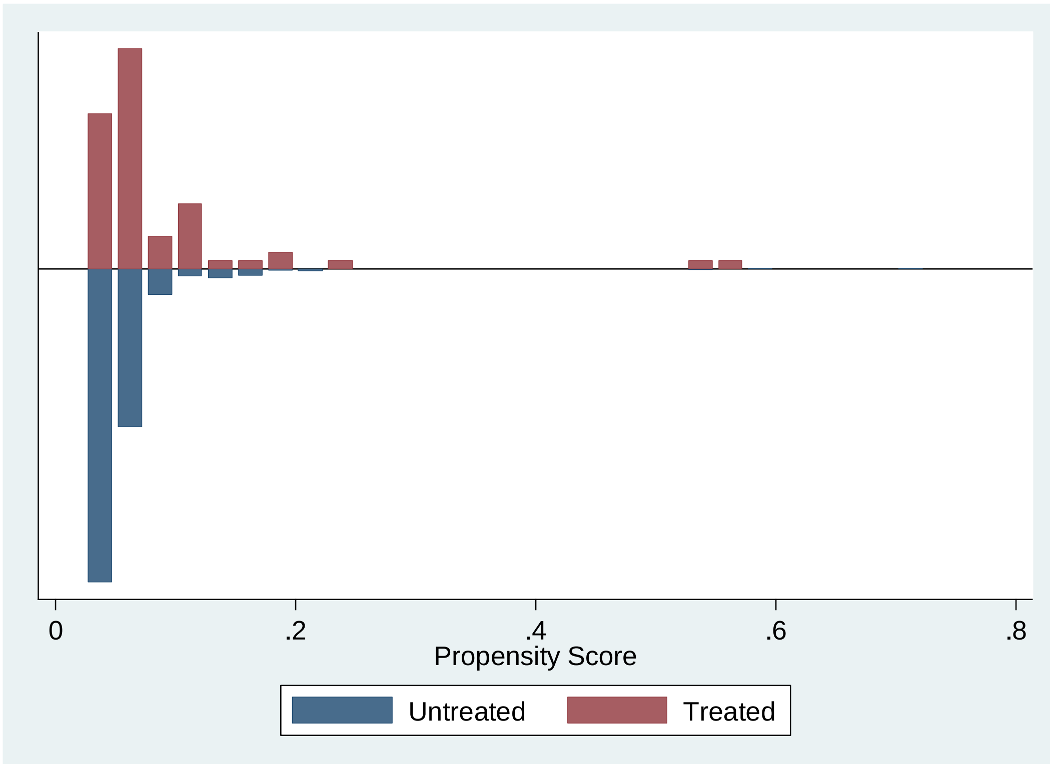
Bin 20 taking into account common support:



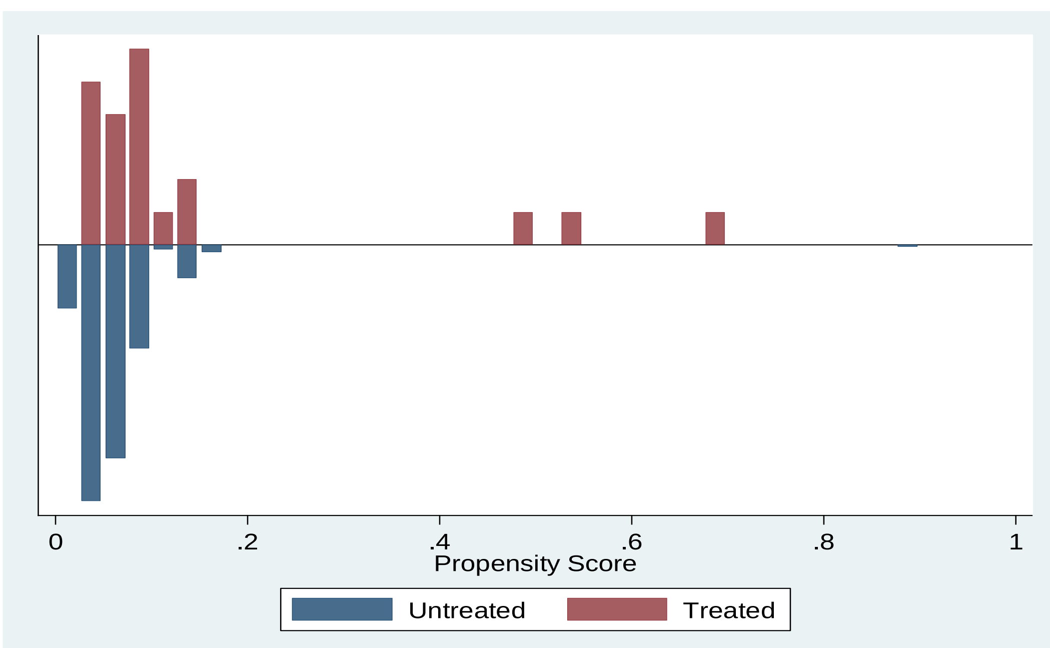
Bin 40 taking into account Common support



Bin 40 without common support restriction



ICT :

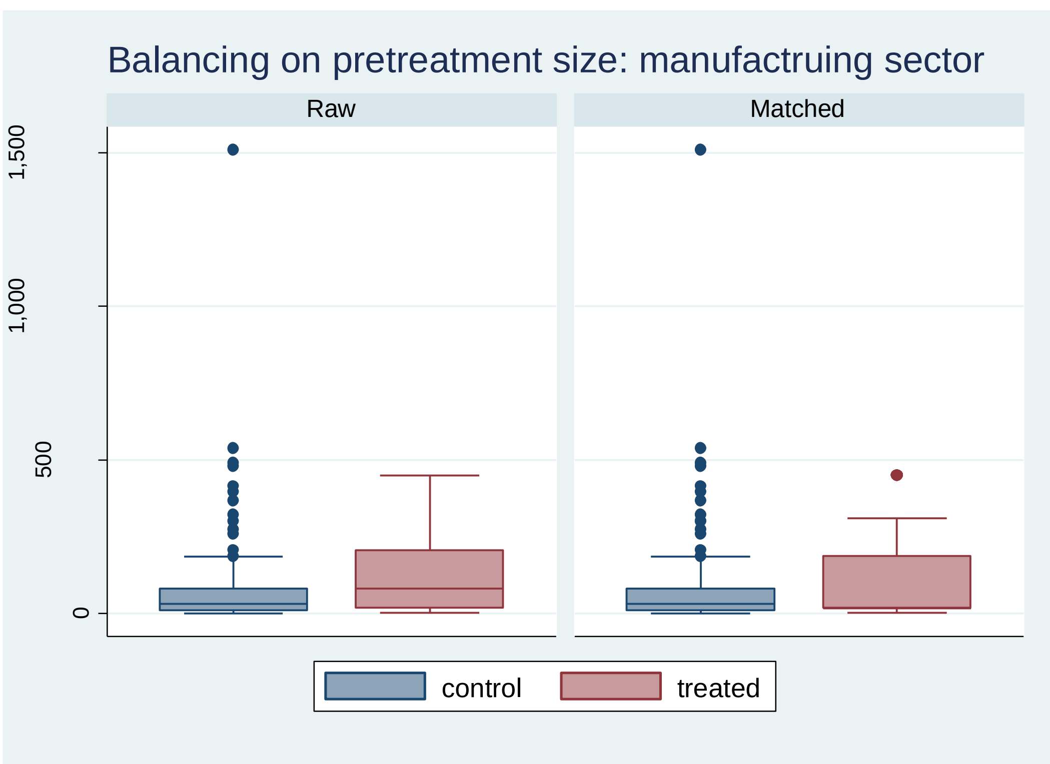


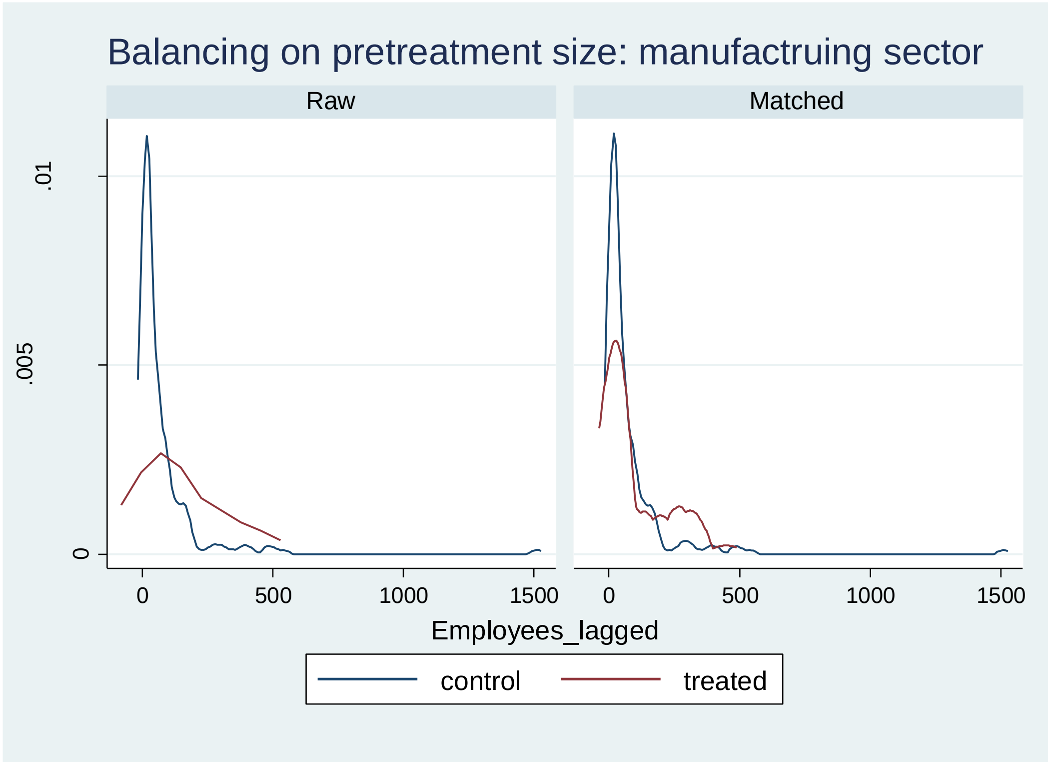
Appendix 3.h

Some examples of summarization and balancing graphs after treatment effect measurement for observables:

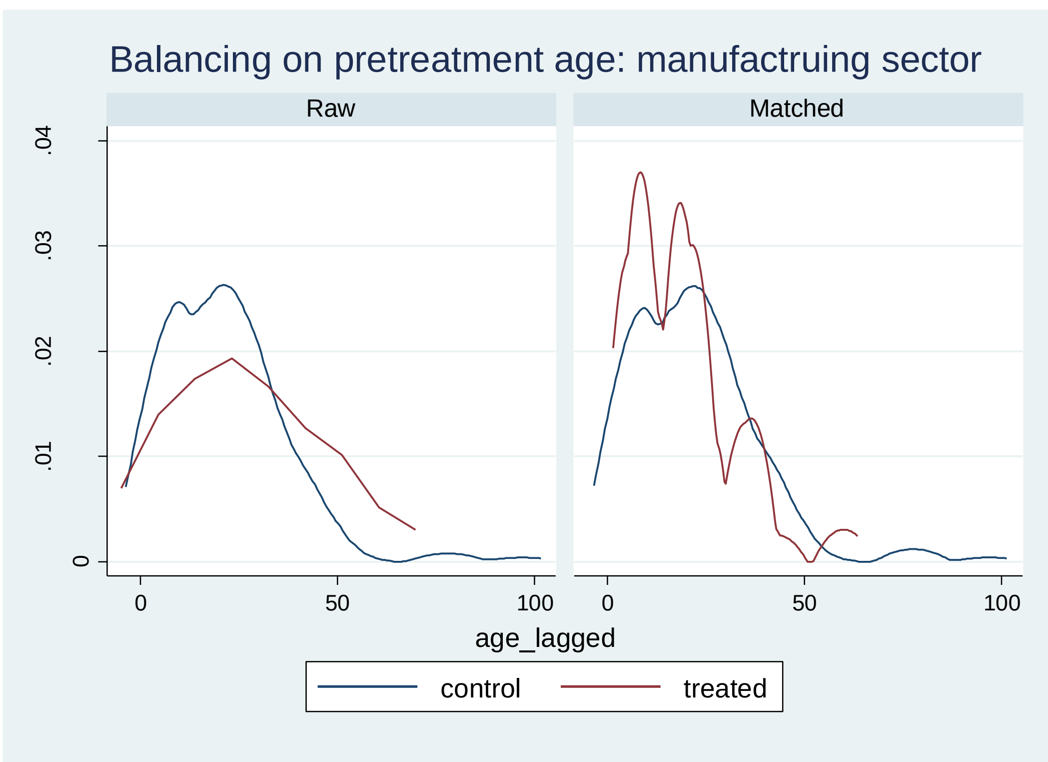
Example: teffects psmatch (tfpch_lagged3) (treatment Employees_lagged age_lagged, probit)

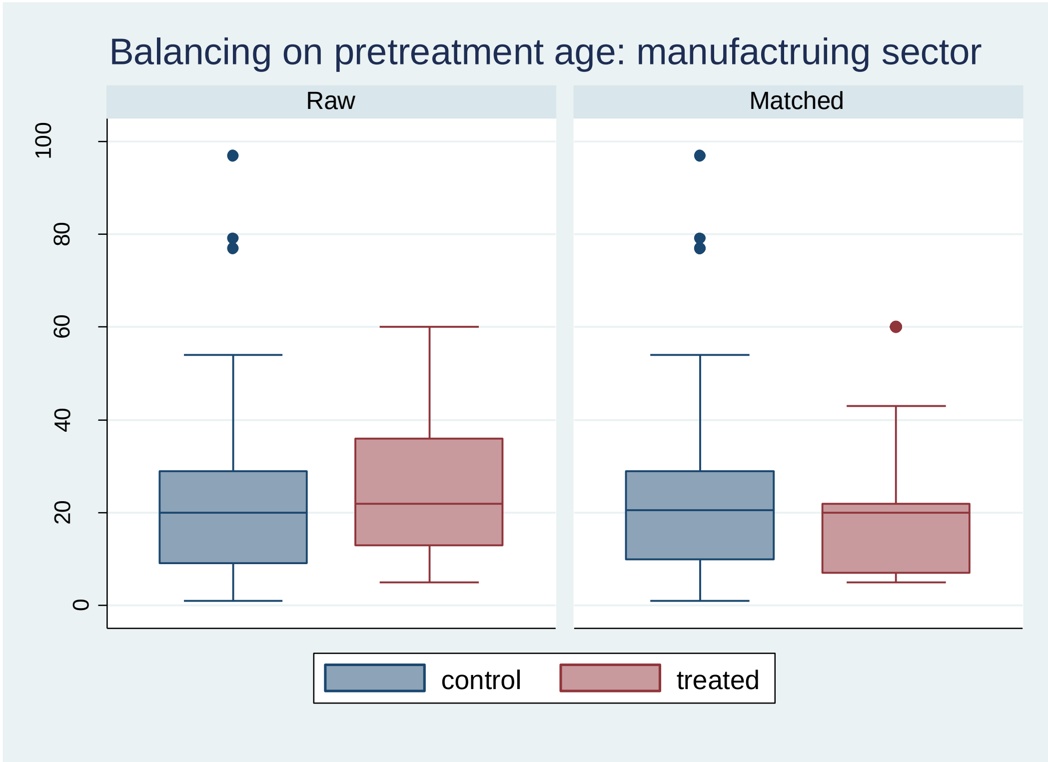
```
. tebalance summarize
note: refitting the model using the generate() option

  Covariate balance summary
                                                     Raw      Matched
                          -----------------------------------------
                          Number of obs =            564        1,128
                          Treated obs   =             36          564
                          Control obs   =            528          564
                          -----------------------------------------

  -----------------------------------------------------------------
                |Standardized differences          Variance ratio
                |        Raw      Matched           Raw     Matched
  ----------------+------------------------------------------------
  Employees_lag~d |   .5802458     .1105861      3.279174    .8700136
       age_lagged |   .3426873    -.1722282      1.154401    .7403386
  -----------------------------------------------------------------
```



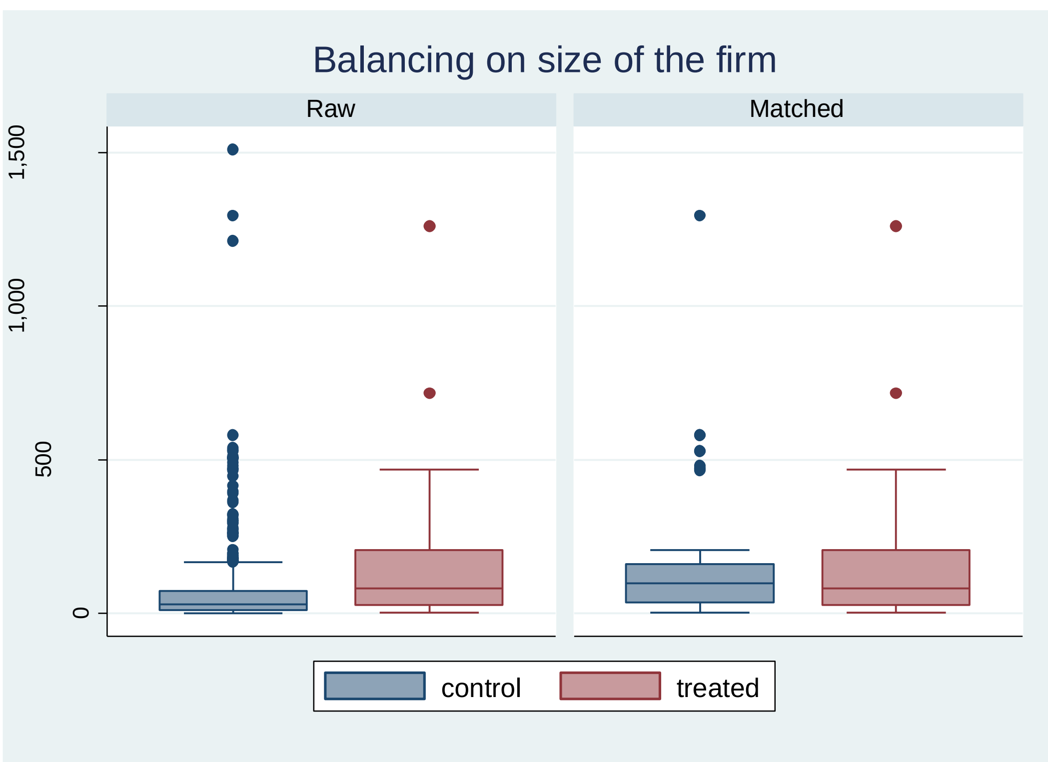


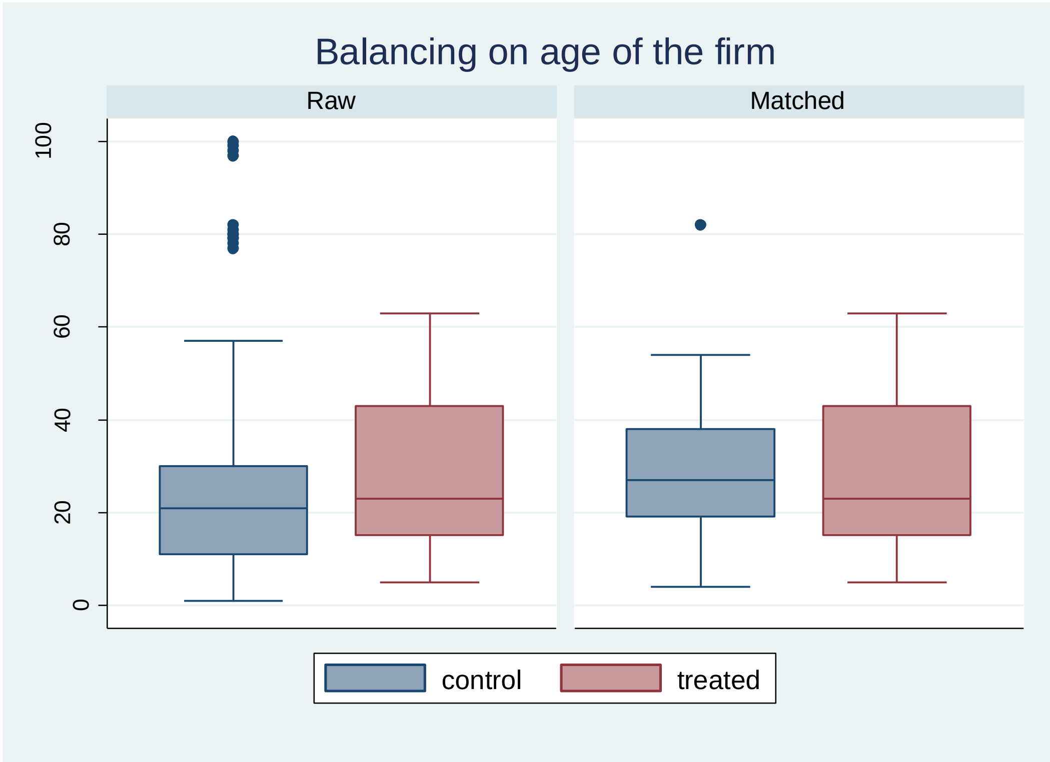
teffects psmatch (effch_lagged5) (treatment Employees_lagged age_lagged)

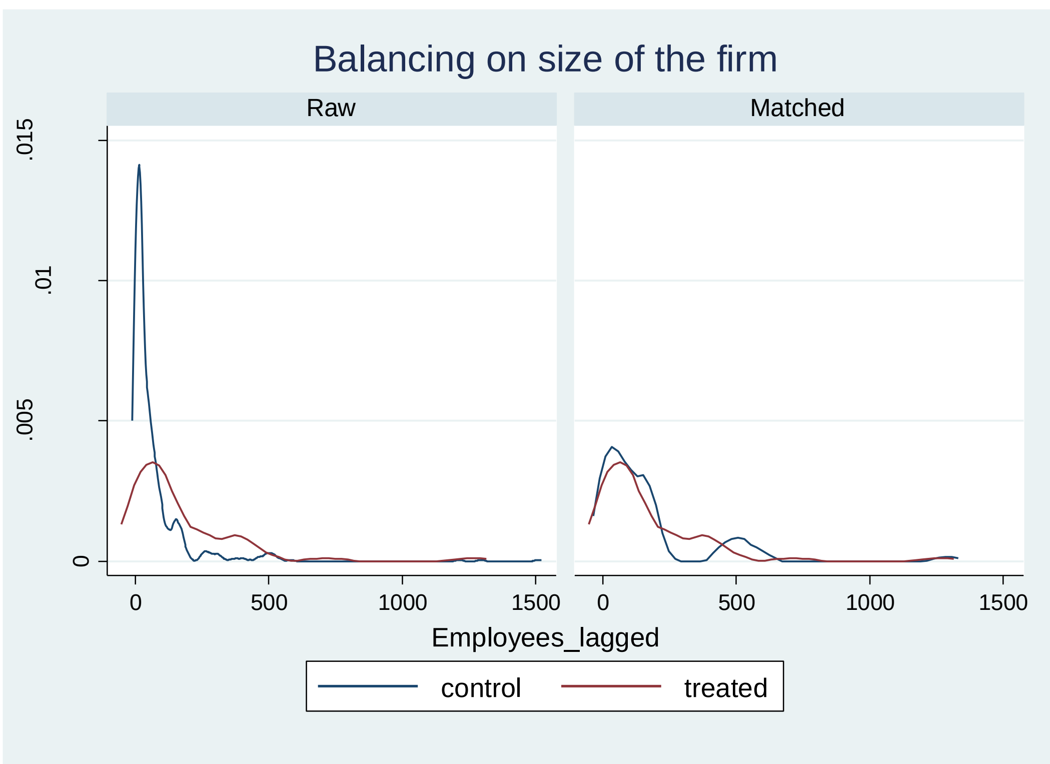


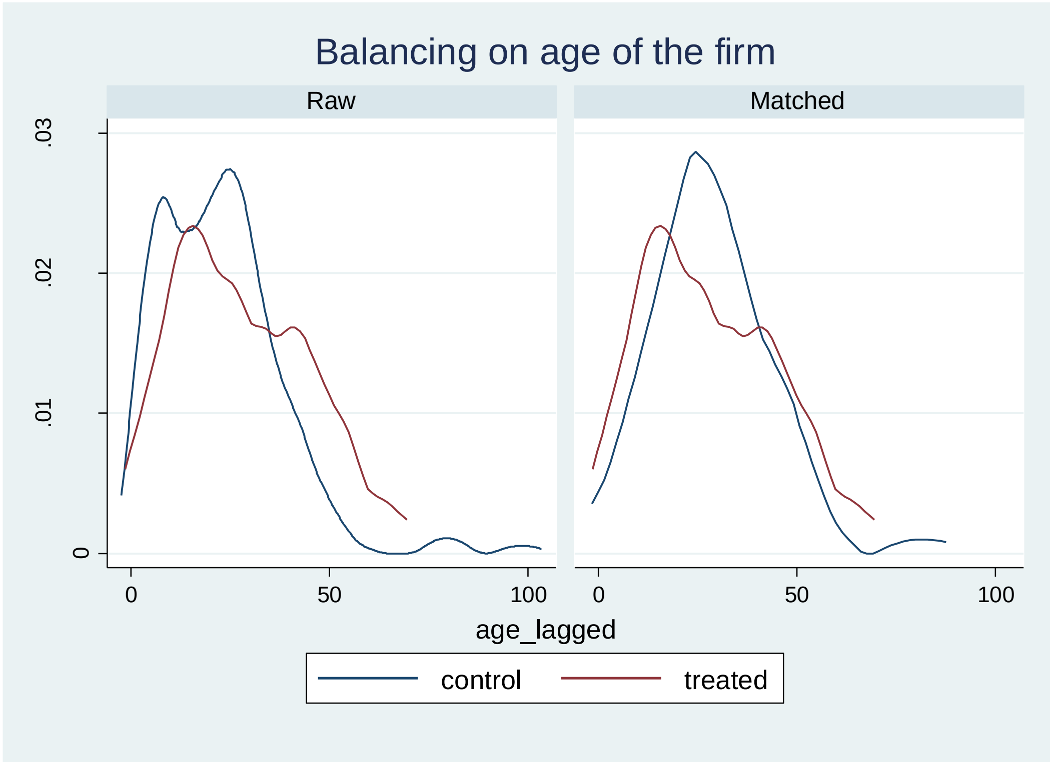


teffects psmatch (tech_lagged2) (treatment Employees_lagged age_lagged)




Balancing on age of the firm
Raw
Matched
100
80
60
40
20
0
control
treated


Balancing on size of the firm
Raw
Matched
.015
.01
.005
0
0
500
1000
1500
0
500
1000
1500
Employees_lagged
control
treated



Fig(s). Other examples of balancing on age and size variables for treated and control using box plot and kernel (after each estimation these balancing graphs can be checked)

Appendix 3.i

Balancing property for each sector: Becker & Ichino (2002)

Manufacturing: Satisfied

```
Estimation of the propensity score

note: INDUS dropped because of collinearity
Iteration 0:   log likelihood = -248.58809
Iteration 1:   log likelihood =  -236.9923
Iteration 2:   log likelihood = -236.27201
Iteration 3:   log likelihood = -236.27168

Probit regression                                 Number of obs   =       1128
                                                  LR chi2(2)      =      24.63
                                                  Prob > chi2     =     0.0000
Log likelihood = -236.27168                       Pseudo R2       =     0.0495
```

treatment	Coef.	Std. Err.	z	P>|z|	[95% Conf. Interval]	
Employees_~d	.0015361	.0003183	4.83	0.000	.0009122	.0021599
age_lagged	.0065512	.0038066	1.72	0.085	-.0009095	.014012
_cons	-1.898106	.12257	-15.49	0.000	-2.138339	-1.657873

```
Note: the common support option has been selected
The region of common support is [.03128198, .57200453]



Description of the estimated propensity score
in region of common support
```

Estimated propensity score

	Percentiles	Smallest		
1%	.031499	.031282		
5%	.0326623	.031282		
10%	.0339764	.0313042	Obs	1,101
25%	.0393853	.0313042	Sum of Wgt.	1,101
50%	.0470862		Mean	.0568674
		Largest	Std. Dev.	.0403814
75%	.0605775	.5267441		
90%	.0790315	.5311844	Variance	.0016307
95%	.1125116	.5454998	Skewness	7.289178
99%	.1887716	.5720045	Kurtosis	80.50567

```
******************************************************
Step 1: Identification of the optimal number of blocks
Use option detail if you want more detailed output
******************************************************


The final number of blocks is 5

This number of blocks ensures that the mean propensity score
is not different for treated and controls in each blocks



**********************************************************
Step 2: Test of balancing property of the propensity score
Use option detail if you want more detailed output
**********************************************************


The balancing property is satisfied


This table shows the inferior bound, the number of treated
and the number of controls for each block
```

Inferior of block of pscore	treatment 0	1	Total
.031282	605	19	624
.05	372	31	403
.1	52	12	64
.2	5	1	6
.4	2	2	4
Total	1,036	65	1,101

```
Note: the common support option has been selected


*******************************************
End of the algorithm to estimate the pscore
*******************************************
```

Construction sector: Not satisfied

```
Step 2: Test of balancing property of the propensity score
Use option detail if you want more detailed output
**********************************************************

Variable age_lagged is not balanced in block 1

The balancing property is not satisfied

Try a different specification of the propensity score
```

Inferior of block of pscore	treatment 0	1	Total
0	309	2	311
.0125	5	2	7
Total	314	4	318

```
Note: the common support option has been selected


*******************************************
End of the algorithm to estimate the pscore
*******************************************
```

Wholesale retail and motor repair: Not satisfied

```
Step 2: Test of balancing property of the propensity score
Use option detail if you want more detailed output
**********************************************************

Variable age_lagged is not balanced in block 1

The balancing property is not satisfied

Try a different specification of the propensity score
```

Inferior of block of pscore	treatment 0	1	Total
0	265	3	268
Total	265	3	268

```
Note: the common support option has been selected


*******************************************
End of the algorithm to estimate the pscore
```

ICT: Satisfied

```
Description of the estimated propensity score
in region of common support
```

Estimated propensity score

	Percentiles	Smallest		
1%	.0330395	.0328728		
5%	.035574	.0330251		
10%	.0385185	.0330395	Obs	250
25%	.0463952	.0332179	Sum of Wgt.	250
50%	.0617212		Mean	.0727386
		Largest	Std. Dev.	.0624388
75%	.0792679	.1668779		
90%	.0998512	.4786346	Variance	.0038986
95%	.1352799	.5350713	Skewness	6.876051
99%	.4786346	.6996633	Kurtosis	60.45748

```
.  pscore treatment Employees_lagged age_lagged INDUS if INDUS==4, pscore(myscore4) comsup


****************************************************
Algorithm to estimate the propensity score
****************************************************


The treatment is treatment
```

treatment	Freq.	Percent	Cum.
0	341	93.68	93.68
1	23	6.32	100.00
Total	364	100.00	

```
Estimation of the propensity score

note: INDUS dropped because of collinearity
Iteration 0:   log likelihood = -76.944953
Iteration 1:   log likelihood = -69.233179
Iteration 2:   log likelihood = -69.022827
Iteration 3:   log likelihood = -69.022675

Probit regression                                 Number of obs   =        312
                                                  LR chi2(2)      =      15.84
                                                  Prob > chi2     =     0.0004
Log likelihood = -69.022675                       Pseudo R2       =     0.1030
```

treatment	Coef.	Std. Err.	z	P>|z|	[95% Conf.	Interval]
Employees_~d	.0033012	.0009081	3.64	0.000	.0015213	.005081
age_lagged	-.0267544	.0129667	-2.06	0.039	-.0521687	-.00134
_cons	-1.309598	.214278	-6.11	0.000	-1.729575	-.8896208

```
Note: the common support option has been selected
The region of common support is [.03287283, .69966332]
```

```
****************************************************
Step 1: Identification of the optimal number of blocks
Use option detail if you want more detailed output
****************************************************


The final number of blocks is 4

This number of blocks ensures that the mean propensity score
is not different for treated and controls in each blocks



********************************************************
Step 2: Test of balancing property of the propensity score
Use option detail if you want more detailed output
********************************************************


The balancing property is satisfied


This table shows the inferior bound, the number of treated
and the number of controls for each block
```

Inferior of block of pscore	treatment 0	1	Total
.0328728	229	18	247
.4	0	2	2
.6	0	1	1
Total	229	21	250

```
Note: the common support option has been selected


******************************************
End of the algorithm to estimate the pscore
******************************************
```

Technical activity sector: Satisfied

```
.  pscore treatment Employees_lagged age_lagged INDUS if INDUS==5, pscore(myscore5) comsup



****************************************************
Algorithm to estimate the propensity score
****************************************************


The treatment is treatment
```

treatment	Freq.	Percent	Cum.
0	334	97.38	97.38
1	9	2.62	100.00
Total	343	100.00	

```
Estimation of the propensity score

note: INDUS dropped because of collinearity
Iteration 0:   log likelihood = -36.723261
Iteration 1:   log likelihood = -36.378728
Iteration 2:   log likelihood = -36.367596
Iteration 3:   log likelihood = -36.367573

Probit regression                                 Number of obs   =        294
                                                  LR chi2(2)      =       0.71
                                                  Prob > chi2     =     0.7007
Log likelihood = -36.367573                       Pseudo R2       =     0.0097
```

treatment	Coef.	Std. Err.	z	P>|z|	[95% Conf. Interval]	
Employees_~d	.0000912	.0011173	0.08	0.935	-.0020988	.0022811
age_lagged	-.0127776	.0162233	-0.79	0.431	-.0445745	.0190194
_cons	-1.724108	.2870681	-6.01	0.000	-2.286751	-1.161465

```
Note: the common support option has been selected
The region of common support is [.0207985, .03698406]
```

```
Description of the estimated propensity score
in region of common support

                 Estimated propensity score
-------------------------------------------------------------
      Percentiles      Smallest
 1%     .0211531       .0207985
 5%     .0218103       .0211438
10%     .0224896       .0211531       Obs                 217
25%      .025366       .0211531       Sum of Wgt.         217

50%     .0298307                      Mean           .0293614
                        Largest       Std. Dev.      .0046711
75%      .033037       .0369546
90%     .0358837        .036962       Variance       .0000218
95%     .0361433       .0369841       Skewness      -.1616813
99%      .036962       .0369841       Kurtosis       1.850818

******************************************************
Step 1: Identification of the optimal number of blocks
Use option detail if you want more detailed output
******************************************************


The final number of blocks is 1

This number of blocks ensures that the mean propensity score
is not different for treated and controls in each blocks



**********************************************************
Step 2: Test of balancing property of the propensity score
Use option detail if you want more detailed output
**********************************************************


The balancing property is satisfied


This table shows the inferior bound, the number of treated
and the number of controls for each block
```

Inferior of block of pscore	treatment 0	1	Total
.0207985	209	8	217
Total	209	8	217

```
Note: the common support option has been selected


*******************************************
End of the algorithm to estimate the pscore
*******************************************
```

```
*********************************************************
Step 2: Test of balancing property of the propensity score
Use option detail if you want more detailed output
*********************************************************


The balancing property is satisfied


This table shows the inferior bound, the number of treated
and the number of controls for each block
```

Inferior of block of pscore	treatment 0	1	Total
.0074703	51	4	55
Total	51	4	55

```
Note: the common support option has been selected


******************************************
End of the algorithm to estimate the pscore
******************************************
```

Description of balancing scores for each industry :

```
. bysort treatment: sum myscore1 myscore22 myscore33 myscore4 myscore5
```

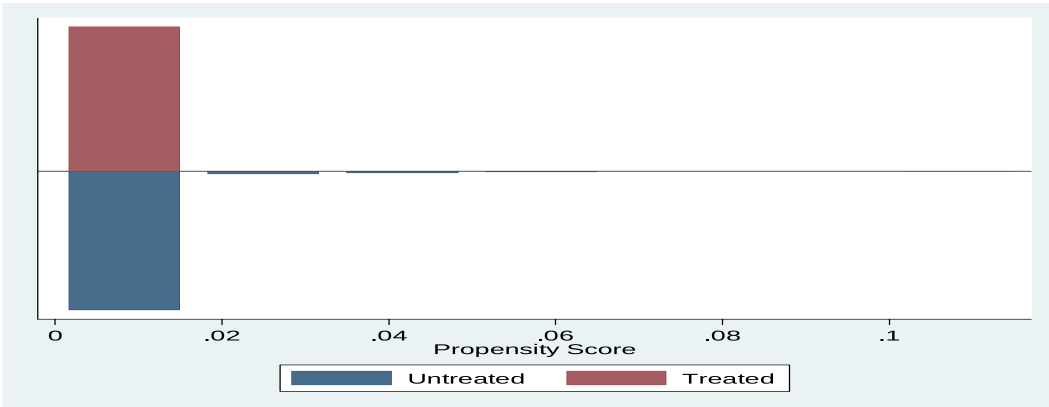
-> treatment = 0

Variable	Obs	Mean	Std. Dev.	Min	Max
myscore1	1,063	.0554998	.0424459	.0299227	.7096618
myscore22	596	.0066879	.0054721	.0043279	.0682215
myscore33	1,221	.0024541	.0015679	.0023467	.0567752
myscore4	291	.0602202	.0567957	.0124469	.8855364
myscore5	286	.0271657	.007758	.0060346	.0401749

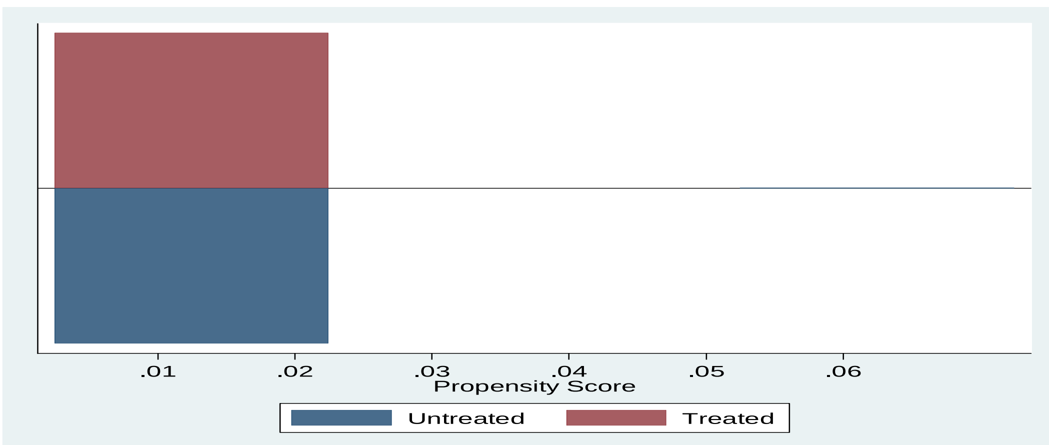
-> treatment = 1

Variable	Obs	Mean	Std. Dev.	Min	Max
myscore1	65	.087386	.0923018	.031282	.5720045
myscore22	4	.0078483	.0005211	.0074703	.0086193
myscore33	3	.002553	.0003188	.002369	.0029212
myscore4	21	.147195	.18338	.0328728	.6996633
myscore5	8	.0290988	.0066779	.0207985	.0369841

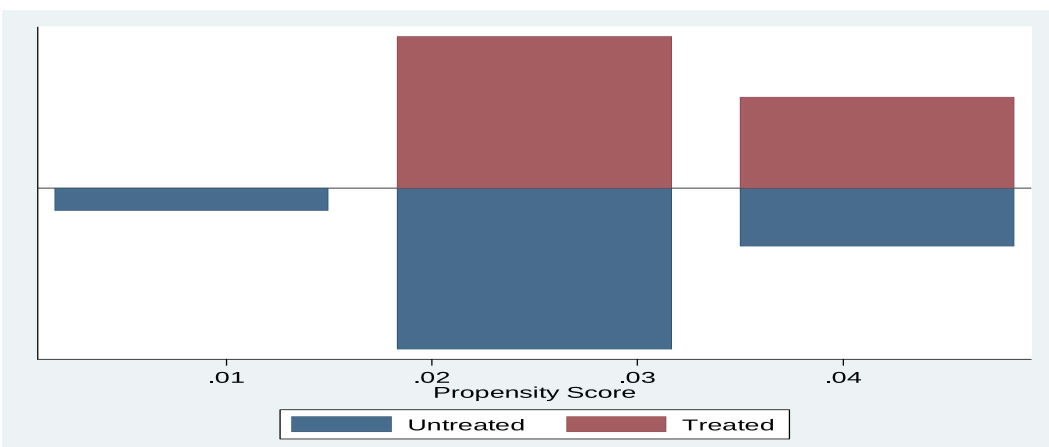
Propensity graphs for construction sector:



Propensity graph for whole sale retail and motor repair sector:



Propensity graph for technical activity sector:



Appendix 3.j

Treatment effect PSM analysis for low-medium and high tech industries:

Low medium tech industries: For ATT no effect at any level But for ATE

```
. teffects psmatch ( tfpch_lagged2 ) (treatment Employees_lagged age_lagged, probit)

Treatment-effects estimation                   Number of obs      =      1,968
Estimator      : propensity-score matching     Matches: requested =          1
Outcome model  : matching                                     min =          1
Treatment model: probit                                       max =          6
------------------------------------------------------------------------------
             |              AI Robust
tfpch_lagg~2 |      Coef.   Std. Err.      z    P>|z|     [95% Conf. Interval]
-------------+----------------------------------------------------------------
ATE          |
   treatment |
   (1 vs 0)  |  -.1522776   .0747305    -2.04   0.042    -.2987466   -.0058085

. teffects psmatch ( tfpch_lagged3 ) (treatment Employees_lagged age_lagged, probit)

Treatment-effects estimation                   Number of obs      =      1,476
Estimator      : propensity-score matching     Matches: requested =          1
Outcome model  : matching                                     min =          1
Treatment model: probit                                       max =          5
------------------------------------------------------------------------------
             |              AI Robust
tfpch_lagg~3 |      Coef.   Std. Err.      z    P>|z|     [95% Conf. Interval]
-------------+----------------------------------------------------------------
ATE          |
   treatment |
   (1 vs 0)  |  -.1738618   .0945426    -1.84   0.066    -.3591618    .0114383
------------------------------------------------------------------------------

. teffects psmatch ( effch_lagged2 ) (treatment Employees_lagged age_lagged, probit)

Treatment-effects estimation                   Number of obs      =      1,968
Estimator      : propensity-score matching     Matches: requested =          1
Outcome model  : matching                                     min =          1
Treatment model: probit                                       max =          6
------------------------------------------------------------------------------
             |              AI Robust
effch_lagg~2 |      Coef.   Std. Err.      z    P>|z|     [95% Conf. Interval]
-------------+----------------------------------------------------------------
ATE          |
   treatment |
   (1 vs 0)  |  -.1824348     .08731    -2.09   0.037    -.3535593   -.0113104
------------------------------------------------------------------------------
```

```
. teffects psmatch ( effch_lagged3 ) (treatment Employees_lagged age_lagged, probit)
```

Treatment-effects estimation Number of obs = 1,476
Estimator : propensity-score matching Matches: requested = 1
Outcome model : matching min = 1
Treatment model: probit max = 5

effch_lagg~3	Coef.	AI Robust Std. Err.	z	P>|z|	[95% Conf.	Interval]
ATE						
treatment						
(1 vs 0)	-.1754034	.1005043	-1.75	0.081	-.3723882	.0215814

```
. teffects psmatch ( effch_lagged5) (treatment Employees_lagged age_lagged, probit)
```

Treatment-effects estimation Number of obs = 492
Estimator : propensity-score matching Matches: requested = 1
Outcome model : matching min = 1
Treatment model: probit max = 1

effch_lagg~5	Coef.	AI Robust Std. Err.	z	P>|z|	[95% Conf.	Interval]
ATE						
treatment						
(1 vs 0)	-.0828584	.0498917	-1.66	0.097	-.1806444	.0149275

```
. teffects psmatch ( techch_lagged4 ) (treatment Employees_lagged age_lagged, probit)
```

Treatment-effects estimation Number of obs = 984
Estimator : propensity-score matching Matches: requested = 1
Outcome model : matching min = 1
Treatment model: probit max = 4

techch_lag~4	Coef.	AI Robust Std. Err.	z	P>|z|	[95% Conf.	Interval]
ATE						
treatment						
(1 vs 0)	-.0858564	.0303198	-2.83	0.005	-.1452821	-.0264307

High tech sectors

```
. table treatment
```

treatment	Freq.
0	675
1	32

```
.

. teffects psmatch ( tfpch_lagged2 ) (treatment Employees_lagged age_lagged, probit),atet

Treatment-effects estimation                 Number of obs      =        404
Estimator      : propensity-score matching   Matches: requested =          1
Outcome model  : matching                                   min =          1
Treatment model: probit                                     max =          5
```

tfpch_lagg~2	Coef.	AI Robust Std. Err.	z	P>|z|	[95% Conf.	Interval]
ATET						
treatment						
(1 vs 0)	.1279439	.0695052	1.84	0.066	-.0082837	.2641716

```
. tebalance summarize Employees_lagged age_lagged
```
note: refitting the model using the **generate()** option

Covariate balance summary

	Raw	Matched
Number of obs =	404	52
Treated obs =	26	26
Control obs =	378	26

	Standardized differences Raw	Standardized differences Matched	Variance ratio Raw	Variance ratio Matched
Employees_lag~d	.5234243	.0866592	1.502455	.6384539
age_lagged	-.2659138	.1266746	.9917175	1.731739

.

```
  Covariate balance summary
                                                              Raw      Matched
                                    ----------------------------------------
                                    Number of obs =          202          404
                                    Treated obs   =            7          202
                                    Control obs   =          195          202
                                    ----------------------------------------

  ---------------------------------------------------------------------
                 |Standardized differences          Variance ratio
                 |        Raw     Matched           Raw    Matched
  ---------------+-----------------------------------------------------
  Employees_lag~d|   .4394891    .3679225      .1454684   .1106402
       age_lagged|  -.2919186    .1186018      1.235487   .9247207
  ---------------------------------------------------------------------

Treatment-effects estimation                   Number of obs      =        303
Estimator      : propensity-score matching     Matches: requested =          1
Outcome model  : matching                                     min =          1
Treatment model: probit                                       max =          3
------------------------------------------------------------------------------
             |              AI Robust
techch_lag~3 |      Coef.   Std. Err.      z    P>|z|     [95% Conf. Interval]
-------------+----------------------------------------------------------------
ATE          |
   treatment |
   (1 vs 0)  |   -.061266   .0260387    -2.35   0.019    -.1123009    -.010231
------------------------------------------------------------------------------

. tebalance summarize Employees_lagged age_lagged
note: refitting the model using the generate() option

  Covariate balance summary
                                                              Raw      Matched
                                    ----------------------------------------
                                    Number of obs =          303          606
                                    Treated obs   =           13          303
                                    Control obs   =          290          303
                                    ----------------------------------------

  ---------------------------------------------------------------------
                 |Standardized differences          Variance ratio
                 |        Raw     Matched           Raw    Matched
  ---------------+-----------------------------------------------------
  Employees_lag~d|   .5197428    .2353534      1.854771   .3980883
       age_lagged|  -.3605517    .0013391      1.063823   .8827313
  ---------------------------------------------------------------------

. teffects psmatch ( techch_lagged4) (treatment Employees_lagged age_lagged, probit)

Treatment-effects estimation                   Number of obs      =        202
Estimator      : propensity-score matching     Matches: requested =          1
Outcome model  : matching                                     min =          1
Treatment model: probit                                       max =          2
------------------------------------------------------------------------------
             |              AI Robust
techch_lag~4 |      Coef.   Std. Err.      z    P>|z|     [95% Conf. Interval]
-------------+----------------------------------------------------------------
ATE          |
   treatment |
   (1 vs 0)  |  -.1111357   .0643207    -1.73   0.084    -.2372019    .0149306
------------------------------------------------------------------------------
```

Appendix 3.k

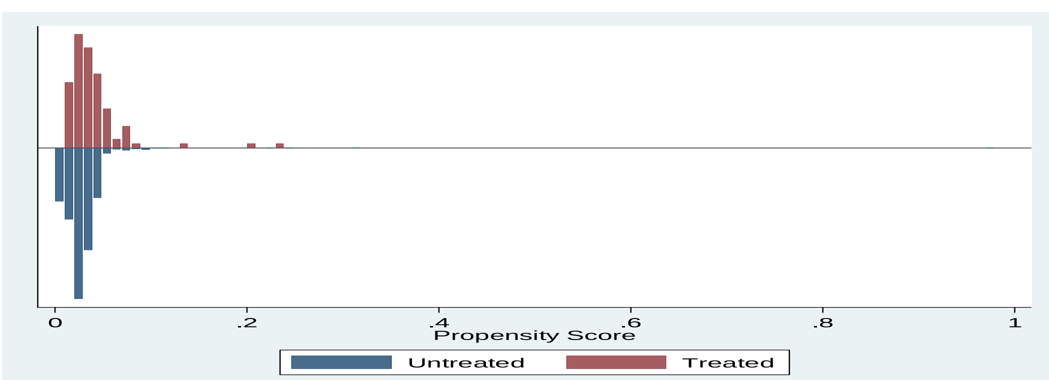
Balancing property for all sectors pooled together: Not satisfied

```
******************************************************
Step 1: Identification of the optimal number of blocks
Use option detail if you want more detailed output
******************************************************


The final number of blocks is 4

This number of blocks ensures that the mean propensity score
is not different for treated and controls in each blocks



**********************************************************
Step 2: Test of balancing property of the propensity score
Use option detail if you want more detailed output
**********************************************************

Variable Employees_lagged is not balanced in block 1

The balancing property is not satisfied

Try a different specification of the propensity score
```

Inferior of block of pscore	treatment 0	1	Total
0	2,806	81	2,887
.05	97	17	114
.1	6	1	7
.2	2	2	4
Total	2,911	101	3,012

```
Note: the common support option has been selected


*******************************************
End of the algorithm to estimate the pscore
*******************************************
```

Prpensity graph for all sectors pooled



Appendix 3.l

R&D subsidies impact measurement by (aggregation level: first digit of ATECO2007)

Sector categorization based on first 3-digit or 2-digit industry and service codes, does not provide a high number of treated and non-treated observations. Therefore, the analysis levels up to 1-digit sector code level. At the same time, particular sectors with at least one R&D subsidization occurred are chosen. Hence, results are generated for seven out of nine categories based on first digit sector code.[126]

The period of sample data analysis is set from 2011 to 2014. In treatment effect analysis; the treatment control variables should refer to at least one year before the treatment and the Malmquist productivity measures should refer to one or two years after the treatment (to hold the assumption that the policy affects the outcome with a lag of one or two years). Therefore, the treatment data of year 2011 and 2014 do not count in the analysis when there is one year lag for the effect. Data on year 2013 is excluded when there is a two-year lag for the effect, hence it only remains treatment data for 2012.

Table (1.3.i) shows the number of total observations with complete data and the proportion of treated and non-treated for different periods by each industry using one-digit code level of aggregation. In the following, the treatment effect results for each single sector are generated. The numbers of treatments (subsidies) happening in the industry for years under analysis are mentioned as well. The method measures the effect of R&D public policy on efficiency change and technical frontier change using propensity score matching. The productivity is also measured using Malmquist Productivity Index method.

Table is referred to link the industries classified under each category of first sector digit. Table (1.3.i) in general implies mixed findings with respect to the effect of policy on productivity measures in both cases of one year and two years lag. There is no effect of policy on efficiency change and technical efficiency change for firms with first sector digits starting with 1, 2 or 3. The number of observations treated in comparison with total observations are very low for sectors 1

[126] In a first run of analysis, four consecutive years from 2011 to 2014 have been chosen. The treatment effect analysis has been provided in the appendix.

Industry with industry's level of aggregation code: ATECO2007	Effect of R&D subsidy on productivity measures (one-year lag)		number treated vs. observations (one-year lag)	Effect of R&D subsidy on productivity measures (two-year lag)		number treated vs. observations (two-year lag)	Total number of Obs.
	Efficiency change	*Technological Change*		*Efficiency change*	*Technological Change*		
starting with digit 1	*0.11*	*0.08*	*6/89*	*-0.03*	*-0.04*	*4/70*	*296*
starting with digit 2	*0.16*	*-0.09*	*36/496*	*0.04*	*-0.05*	*28/248*	*992*
starting with digit 3	-	-	*2/55*	-	-	*1/27*	*112*
starting with digit 4	*-0.39****	*0.09*	*6/848*	*-0.05*	*0.13**	*3/424*	*1,696*
starting with digit 5	-	-	-	-	-	-	*124*
starting with digit 6	*0.00*	*0.02*	*26/252*	*-0.07*	*0.01*	*23/126*	*504*
starting with digit 7	*0.72*	*0.08*	*6/108*	*-0.26****	*0.14***	*4/54*	*216*

**90% level of confidence*
***95% level of confidence*
****99% level of confidence*

Table 3.l.1. Treatment Effect analysis by sector (aggregation level: first digit of ATECO2007)

and 3. However, firms with first digit 2 have a higher proportion of treated versus total observations.

The number of treated firms in category 3 is quite low (1 firm), so that treatment effect results using propensity score matching cannot be generated. Moreover, the number of treated firms in category 1 is not that large. The number of total observations treated in category 2 are 28 treated out of 248 total observations, when the outcome variable is lagged for two years. The number of treated observations would increase to 36 out of 496 if the lag decrease to one year.

Firms with first sector classification digit 4 (category 4) show a negative impact of policy on efficiency change (in case of one-year lag) and a positive impact of policy on technological (technical frontier) change. Although the number of treated in this category is not as high as category 2, however the highest number of non-treated observations can at least make matching more effective. The same as category 3, number of treated firms in category 5 is pretty low that treatment effect using propensity score matching is not feasible.

The results for industry 6 show there is no significant effect of the policy on productivity measures in both cases of one year and two years lag. The number of total observations treated in this category are 23 treated out of 126 total observations, when the outcome variable is lagged for two years. The proportion increases to 26 out of 252 if the lag decrease to one year.

In 7th category, the policy shows significant negative effect on efficiency change in contrast to a positive effect on technological change when the outcome variable (efficiency and technological changes) are being lagged for two years. It means the policy shows significant impact on target indices after two years. Results do not imply any significant effect of the policy on the measures when there is one year lag. The number of treated observations in the first case is 4 out of 54 total observations, while this increases to 6 out of 108 observations when we assume one year lag of policy effect.

The results based on data categorized by first digit sector code, show mixed findings regarded to the impact of R&D subsidies on efficiency change and technical frontier change. However, in cases when the effect is statistically significant it is observed that the subsidy allocation to a firm impacts negatively on relative efficiency change, while it shows a positive influence on the technical frontier. This means a certain firm treated, may perform less efficient relative to the best performers while the frontier (best performers) may move the frontier up receiving the subsidy. One interpretation is relative efficient firms in categories showing significant results, are more capable to apply the grants received into production improvement using R&D inputs and outcomes rather than their followers. However, the lag time is not quite long in this setting to investigate whether the same happens in long-run or not.

Impact evaluation based on first sector code digit explained in this section suffers a serious drawback. The first digit classification includes different non-related industries into one category which may violate the assumption of homogenous operating process to measure relative (in)efficiency and frontier measures. Therefore, to solve this problem, the following section classifies enterprises simply based on the industry they belong to using our elaboration of industry categorization based on sector code (ateco2007). The codes and commands to do such a categorization are provided. As previously noted, there are overlaps between sectors based on Ateco2007 first one digit classification. Referred to table (6) in the main text, in order to measure the impact of R&D subsidies classifying firms based on the exact industry provides us more precise results in comparison with impact evaluation based on first sector digit level of aggregation.

Appendix 4.a

Dataset construction procedures

Dataset constructed to estimate the model includes different variables to be used in different equations. The number of non-missing observations for each variable in each primary dataset (figure1), beside the equations the variable get involved, have been shown in table (4.a.1). The age is calculated by subtracting the year of establishment (inizzio-anno) from the year of the analysis (2008-2010). The sale variable is labeled as cod_280 in PITAGORA balance sheet dataset. The amount of sale for four firms equals to zero. The lowest minimum amount higher than 0, is 4380 Euros. Number of employees can be fractional as the employee number is calculated according to the duration and months of the dependent employees (variable labeled as 'dip' in the primary dataset) and independent employees (labeled as 'ind') within the whole year. Four firms employed more than 1000 employees and two firms more than 3000. Independent employees as a possible proxy for board of the firm ranges from minimum one to maximum eight employees. 184 firms out of 379 firms and 160 out of 301 firms which have responded to RS survey are exporting corporations. There is a variable representing the previous subsidies. The base year for counting up the subsidy allocations is 2005; e.g. a firm being allocated subsidies in 2005, 2007 and 2008 possesses the previous application variable value of 3 in year 2009. The R&D expenditure variable refers to R&D investment variable (labeled C2_01) in R&D survey. However, there are other different variables in R&D survey related to R&D spending which can be used as proxy for R&D investment.

Each firm in the dataset is identified by a unique fiscal code which is a categorical 11-digit string variable. Domain of each firm is also provided. The primary dataset also includes the response to R&D questionnaire defined by a flag variable and the variable to show if the firm has been treated by an R&D subsidy. If there is data available to unsuccessful applications then the minimum amount of subsidy becomes zero. However, the data set obtains all accepted subsidy applications and there is the assumption that all the firms with application have been received and assigned subsidies. Four outlier observations were primarily dropped as the subsidy rate turned out to be higher than one (100%). The evaluation procedure dummy variable is defined and categorized as the previous chapter. Three dummy levels based on this categorization have been defined for this variable.

Table 4.a.1. variables used to estimate the model and the number of non-missing values for each variable

Variable	*R&D investment equation*	*Subsidy rate equation*	*Application decision equation*	*Number of Observations without any missing value*	*Number of observations in RS surveyed without any missing value*	*R&D Subsidized*	*Number of Subsidized firms responded to RS survey*	*Minimum*	*Maximum*
Employees	✓	✓	✓	*361*	*300*	*118*	*57*	*1*	*3515*
firm's age	✓	✓	✓	*342*	*285*	*111*	*54*	*0*	*62*
Sale	✓	✓	✓	*319*	*268*	*105*	*54*	*0*	*676,495,20€*
Total R&D	✓	_	_	_	*301*	_	_	*2000 €*	*5,518,000€*
Industrial sector	✓	✓	✓	*360*	*301*	*116*	*57*	_	_
Geographical position	_	_	_	*359*	*300*	*116*	*57*	_	_
Evaluation procedure	_	✓	_	_	_	*135*	*57*		
Subsidy rate	_	✓	_	_	_	*135*	*57*	*0.05*	*0.83*
Previous treatments	_	✓	✓	_	_	*135*	*57*	*0*	*6*
Export Dummy	_	_	✓	*0* *1*	*0* *1*	*0* *1*	*0* *1*	*1,255€*	*159,210,36€*
				195 *184*	*141* *160*	*75*	*21* *36*		
Total				*379*	*301*	*135*	*57*		

Source: Elaboration on merged datasets on R&D subsidies and firm balance sheet provided by ISPAT (APIAE, PITAGORA and ASIA datasets)

There are also extra information on the geographical position (city) and whether the firm is artisan (handicraft production) or not. Table (4.a.2) displays summary statistics of explanatory variables for potential applicants used in the model. Table (4.a.3) conditions the statistics on the status of being subsidized or not receiving subsidies.

Table (4.a.3) provides descriptive data on variables related to R&D investment, the subsidy rates and application status.

Table 4.a.2 Descriptive statistics of variables for all potential applicants

Variable	***Observations***	***Mean***	***Std. Dev.***	***Minimum***	***Maximum***
Size	*361*	*95.57*	*292.87*	*1*	*3515*
Age	*342*	*18.44*	*13.81*	*0*	*62*
Sales per employee	*319*	*295616.9*	*776354.5*	*0*	*9,042,264*
Board Size	*357*	*1.27*	*0.96*	*1*	*8*
Exporter (Dummy)	*379*	*0.48*	*0.50*	*0*	*1*
SME	*379*	*0.61*	*0.48*	*0*	*1*
Number of Previous Applications	*135*	*0.83*	*1.41*	*0*	*6*
Total	***379***				

Source: Community Innovation Survey (CIS) provided by ISPAT and dataset on grants assigned for applied research projects provided by APIAE

Table 4.a.3 Descriptive statistics for All firms doing R&D, Subsidized firms and non-subsidized firms

	All potential applicants				Subsidized applicants				Non-Subsidized firms			
	Mean	Std. Dev.	Min.	Max	Mean	Std. Dev.	Min	Max	Mean	Std. Dev	Min.	Max.
Planned R&D investment					1,475,312	1,806,123	48,559	10,300,000				
R&D Expenditures (year)	550,588	808,750	4000	5,521000	811,351	962,349	7000	4,111,000	489,672	757,891	4000	5,521,000
Subsidy rate					0.55	0.24	0.05	0.83				
Subsidy amount					1,475,312	1,806,123	7,234	5,606,350				
Evaluation method					2.08	0.66	1	3				
Number of observation		301				57				244		

Source: APIAE dataset provided by ISPAT (All amounts are in €

Appendix 4.b

Equation for Expected subsidy rate based on the firm's belief of the evaluation process

The official scheme for subsidy allocation by APIAE yields the expected rate of subsidy by the firm for the planned R&D project. The equation shows how the firm calculates the expected subsidy rate which is used to estimate the application decision equation:

$$E(s_i) = \Big\{\Big[Research_i * \Big[\Big(\big(0.6 + (0.1 * PRP_i) + (0.1 * Max_i)\big) * Small_i\Big) + \big((0.55 + (0.05 * PRP_i) + (0.1 * Max_i) + (0.05 * PRP_i * Max_i)) * Medium_i\big) + \Big(\big(0.45 + (0.05 * PRP_i) + (0.2 * Max_i) - (0.05 * PRP_i * Max_i)\big) * Large_i\Big)\Big]\Big] + \Big[Development_i * \Big[\big((0.4 + (0.05 * PRP_i) + (0.1 * Max_i) + (0.05 * PRP_i * Max_i)) * Small_i\big)\big) + \Big(\big(0.3 + (0.05 * PRP_i) + (0.1 * Max_i) + (0.05 * PRP_i * Max_i)\big) * Medium_i\Big) + \Big(\big(0.2 + (0.05 * PRP_i) + (0.1 * Max_i) + (0.05 * PRP_i * Max_i)\big) * Large_i\Big)\Big]\Big]\Big\}$$

Where:

$Research_i$; $Development_i$: $Variables\ defining\ the\ type\ of\ R\&D\ project\ which\ is\ realized\ by\ the\ agency.$

$Small_i$; $Medium_i$; $Large_i$: $Dummy\ variables\ determining\ the\ size\ of\ the\ firm\ applying\ for\ the\ contribution$

PRP_i: $PRP_i = 1\ in\ case\ of\ long\ term\ effect\ in\ Provincial\ Research\ Program\ and\ PRP_i = 0\ in\ case\ of\ no\ long\ term\ effect$

Max_i: $Max_i 1\ in\ case\ the\ agency\ decides\ to\ allocate\ the\ maximum\ subsidy\ rate\ possible\ to\ a\ project\ otherwise\ Max_i = 0$

Appendix 4.c

Checking for correlation matrix and multicollinearity in estimations:

Subsidy rate equation:

Evaluation method independent variable:

```
. regress S_rate age  i.SME sales_to_employee  i.ExportFlag  i.industry_code i.ev_method
```

Source	SS	df	MS
Model	3.50837486	10	.350837486
Residual	.809880346	83	.009757595
Total	4.3182552	93	.046432852

Number of obs	=	94
F(10, 83)	=	35.96
Prob > F	=	0.0000
R-squared	=	0.8125
Adj R-squared	=	0.7899
Root MSE	=	.09878

S_rate	Coef.	Std. Err.	t	P>|t|	[95% Conf.	Interval]
age	.0001773	.0008333	0.21	0.832	-.0014801	.0018346
1.SME	-.0512186	.0257146	-1.99	0.050	-.1023638	-.0000733
sales_to_employee	-6.21e-09	9.11e-09	-0.68	0.497	-2.43e-08	1.19e-08
1.ExportFlag	-.0059116	.0285466	-0.21	0.836	-.0626897	.0508665
industry_code						
F	.0420771	.0487231	0.86	0.390	-.0548312	.1389854
G	-.3735365	.1044427	-3.58	0.001	-.5812687	-.1658042
J	-.0498372	.0316174	-1.58	0.119	-.112723	.0130486
M	-.0143052	.0511725	-0.28	0.781	-.1160853	.0874748
ev_method						
2	.4219752	.0291488	14.48	0.000	.3639993	.4799511
3	.5221579	.0381843	13.67	0.000	.4462108	.5981049
_cons	.206554	.0384834	5.37	0.000	.1300121	.283096

```
. pwcorr S_rate age  SME sales_to_employee  ExportFlag  industry_code ev_method
```

	S_rate	age	SME	sales_~e	Export~g	indust~e	ev_met~d
S_rate	1.0000						
age	-0.3600	1.0000					
SME	-0.2418	0.2711	1.0000				
sales_to_e~e	-0.0159	-0.0513	0.0291	1.0000			
ExportFlag	-0.4100	0.2885	0.3043	0.0196	1.0000		
industry_c~e	0.2952	-0.4420	-0.2540	0.0917	-0.5606	1.0000	
ev_method	0.8104	-0.3725	-0.2039	-0.0316	-0.4755	0.4538	1.0000

Regression without evaluation method variable:

Subsidy rate equation:

```
. regress S_rate age  i.SME sales_to_employee  i.ExportFlag  i.industry_code
```

Source	SS	df	MS			
				Number of obs	=	94
				F(8, 85)	=	3.89
Model	1.15809849	8	.144762311	Prob > F	=	0.0006
Residual	3.16015671	85	.037178314	R-squared	=	0.2682
				Adj R-squared	=	0.1993
Total	4.3182552	93	.046432852	Root MSE	=	.19282

S_rate	Coef.	Std. Err.	t	P>|t|	[95% Conf.	Interval]
age	-.0025757	.0015869	-1.62	0.108	-.0057308	.0005795
1.SME	-.047313	.0501189	-0.94	0.348	-.1469628	.0523367
sales_to_employee	-7.18e-09	1.75e-08	-0.41	0.682	-4.20e-08	2.76e-08
1.ExportFlag	-.0875002	.054585	-1.60	0.113	-.1960299	.0210294
industry_code						
F	.1852897	.0841098	2.20	0.030	.018057	.3525224
G	-.1874329	.2021028	-0.93	0.356	-.5892674	.2144015
J	.0266686	.0602507	0.44	0.659	-.093126	.1464632
M	.0831483	.098172	0.85	0.399	-.112044	.2783406
_cons	.6267519	.05328	11.76	0.000	.5208171	.7326868

Appendix 4.d

Investment equation:

Actual annual R&D investment:

```
. regress new_investment_variable age log_employee sales_to_employee independent_employee i.ExportFlag i.indu
> stry_code

      Source |       SS           df       MS      Number of obs   =        48
-------------+----------------------------------   F(9, 38)        =      3.37
       Model |  41.2599119         9  4.58443465   Prob > F        =    0.0040
    Residual |  51.6462477        38  1.35911178   R-squared       =    0.4441
-------------+----------------------------------   Adj R-squared   =    0.3124
       Total |  92.9061595        47   1.9767268   Root MSE        =    1.1658

------------------------------------------------------------------------------------
new_investment_var~e |      Coef.   Std. Err.      t    P>|t|     [95% Conf. Interval]
---------------------+--------------------------------------------------------------
                 age |  -.0146216   .0139597    -1.05   0.302    -.0428816    .0136384
        log_employee |   .5348276   .1499085     3.57   0.001     .2313538    .8383014
   sales_to_employee |   1.18e-07   1.77e-07     0.67   0.508    -2.40e-07    4.77e-07
independent_employee |   .2183062   .4466029     0.49   0.628     -.685794    1.122407
        1.ExportFlag |   .5623859   .5352322     1.05   0.300     -.521135    1.645907
                     |
       industry_code |
                  F  |    -1.8661   1.225689    -1.52   0.136    -4.347378     .615178
                  G  |  -1.061583   1.213314    -0.87   0.387    -3.517809    1.394643
                  J  |  -.3008591   .5473274    -0.55   0.586    -1.408865    .8071472
                  M  |   .6108419   1.981574     0.31   0.760    -3.400644    4.622328
                     |
               _cons |   3.009319   .7563116     3.98   0.000     1.478247    4.540392
------------------------------------------------------------------------------------


. pwcorr new_investment_variable age log_employee sales_to_employee independent_employee ExportFlag industry_
> code

             | new_in~e      age log_em~e sales_~e indepe~e Export~g indust~e
-------------+---------------------------------------------------------------
new_invest~e |   1.0000 
         age |   0.2184   1.0000 
log_employee |   0.5540   0.5143   1.0000 
sales_to_e~e |   0.1869  -0.0513   0.0209   1.0000 
independen~e |  -0.0320   0.2430   0.0944   0.0297   1.0000 
  ExportFlag |   0.4330   0.2885   0.4506   0.0196   0.1110   1.0000 
industry_c~e |  -0.1969  -0.4420  -0.3798   0.0917  -0.1015  -0.5606   1.0000
```

Planned-investment

```
. regress dependent_PlannedInvestment_var age log_employee sales_to_employee independent_employee i.ExportFla
> g i.industry_code
```

Source	SS	df	MS
Model	72.6182929	9	8.06869921
Residual	69.4900263	84	.827262218
Total	142.108319	93	1.52804644

Number of obs	=	94
F(9, 84)	=	9.75
Prob > F	=	0.0000
R-squared	=	0.5110
Adj R-squared	=	0.4586
Root MSE	=	.90954

dependent_PlannedI~r	Coef.	Std. Err.	t	P>|t|	[95% Conf.	Interval]
age	-.026984	.0082634	-3.27	0.002	-.0434168	-.0105513
log_employee	.622153	.0950685	6.54	0.000	.4330989	.8112071
sales_to_employee	2.25e-07	8.29e-08	2.71	0.008	5.98e-08	3.90e-07
independent_employee	-.203304	.2425324	-0.84	0.404	-.6856064	.2789983
1.ExportFlag	.0481237	.2700246	0.18	0.859	-.4888498	.5850971
industry_code						
F	-1.006433	.3955759	-2.54	0.013	-1.793079	-.2197872
G	-.6344573	.9328019	-0.68	0.498	-2.489436	1.220522
J	-.0129004	.2839719	-0.05	0.964	-.5776096	.5518088
M	-.2023013	.472193	-0.43	0.669	-1.141309	.7367063
_cons	11.38177	.4120452	27.62	0.000	10.56237	12.20116

```
. vif
```

Variable	VIF	1/VIF
age	1.70	0.586889
log_employee	2.13	0.469891
sales_to_e~e	1.16	0.859329
independen~e	1.03	0.972059
1.ExportFlag	2.06	0.484777
industry_c~e		
5	1.23	0.816008
6	1.04	0.960969
7	1.59	0.629040
8	1.28	0.783740
Mean VIF	1.47	