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The effects of public support schemes on small and medium enterprises

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ABSTRACT

In this paper we will investigate the effects of direct grants and tax incentives on recipient small and medium enterprises (SMEs). Direct grants and tax incentives are two different public instruments used to correct market failure and facilitate innovation through lowering the cost of R&D. Although large and small firms innovate in different ways, so far limited empirical evidence has been reported with respect to the effectiveness of public R&D instruments for SMEs. Our data suggests that direct subsidies used alone or with tax incentives strengthen the R&D orientation of the SME as well as some aspects of innovation output and absorptive capacity. Although the effects of policy measures are significant when comparison is made to firms that did not use any of the two instruments, not much difference is found when users of direct grants are compared to those who used both the grants and the tax incentives. This result indicates the existence of limitations in the use of tax incentives by SMEs, and thus suggests that subsidies may be the primary instrument in SMEs.

1. Introduction

In this paper we investigate the effects of direct grants and tax incentives, two different public instruments used to correct market failure and facilitate innovation. (The terms direct grant and direct subsidy are used interchangeably to denote a payment made usually by government agencies or local authorities to companies in order to subsidize the cost of a specific R&D or innovation project). While direct subsidy programs are generally intended to support commercial R&D projects with large expected social benefits but inadequate expected returns for private investors (Klette et al., 2000), a tax incentive is a tool for encouraging private R&D expenditure in companies. Traditionally, the majority of studies have focused on determining the impact of public instruments on R&D expenditures. As it was recognized that this aspect by itself does not sufficiently explain the effect of public instruments on innovation in firms, the focus shifted to include the impact of public instruments on innovation output, and changes in firms' innovation-related behavior (Clarysse et al., 2009). However, studies that deal with alterations in firms' innovation output and behavior remain scarce.

Existing literature presents evidence of the usefulness of both tax incentives and direct grants, but the overwhelming majority of these studies focus on only a single instrument as opposed to both. Studies that consider the joint use of these instruments are very scarce (Busom et al., 2014; Bérubé and Mohnen, 2009). The effectiveness of these public policy measures is of particular relevance for small and medium enterprises (SMEs), which rely on innovation to an even greater extent than large firms and are less able to appropriate rents associated with innovation (Fritz, 1989; Sweeney, 1983). This paper adopts the European Commission definition of SME as a company that employs less than 250 employees and has a turnover of less than 50 million Euros. Taking into account that SMEs comprise a large part of most economies, it is fair to state that the impact of public instruments on SMEs requires special consideration.

In this paper we seek to contribute to the literature on public support schemes in four ways. First, we focus purely on SMEs seeking to contribute to the understanding of how public instruments affect these companies. We also consider the effects of subsidies (alone or used jointly in combination with tax incentives) on a number of R&D and innovation variables compared to firms which underwent no treatment. Thus far not much empirical evidence has been provided with respect to the effectiveness of R&D instruments on small and medium-sized firms (Romero-Jordán et al., 2014; Czarnitzki and Lopes-Bento, 2013; Reinkowski et al., 2010; Herrera et al., 2010). The closest to our paper is the study by Hottenrott and Lopes-Bento (2014), which demonstrates that R&D subsidies aimed at incentivizing collaboration in SMEs improve innovation performance. As compared to Hottenrott and

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Lopes-Bento (2014), in our paper we examine the effects of R&D subsidies used alone or with tax incentives on innovation output. Additionally, we include more output variables such as the number of employees in R&D, R&D intensity, the number of innovations as well as the percentage they represent in sales, and the effects of public instruments on absorptive capacity.

Second, since large and small firms innovate in different ways, the same policy may affect large firms and SMEs differently. Due to the specific features of each instrument, in SMEs direct grants can be expected to be favored over tax incentives. For example, Busom et al. (2014) show that financially constrained SMEs prefer subsidies over tax incentives, and suggest that tax incentives may not be effective in resolving appropriability concerns in SMEs. Based on these findings we hypothesize that in SMEs subsidies may be a primary policy instrument, while tax incentives serve more as a fill-in to cover less demanding projects. To confirm this hypothesis, we compare the use of subsidies alone with the joint use of subsidies and tax incentives, and examine to what extent the addition of tax incentives contributes to R&D, innovation output and absorptive capacity.

The third contribution we attempt to make in this paper is to show that the effects of public instruments affect the recipient firm on a deep level by affecting crucial firm capabilities such as absorptive capacity. Any firm can be viewed as a bundle of tangible and intangible resources and capabilities (Wernerfelt, 1984; Eisenhardt and Schoonhoven, 1996), where resources can be defined as financial, physical, human, commercial, technological, and organizational assets used by the firm, and capabilities refer to the firm's capacity to deploy and coordinate different resources (Grant, 1996; Amit and Schoemaker 1993). In this paper we focus on absorptive capacity which is one of the most important firm capabilities; it is defined as a firm's ability to recognize the value of new information, assimilate it, and apply it for commercial purposes (Cohen and Levinthal, 1990). Absorptive capacity influences the creation of other organizational competencies and provides the firm with multiple sources of competitive advantage (Barney, 1991). This capacity is developed cumulatively: it depends on the level of prior knowledge and is advanced through a process of knowledge accumulation which happens through various activities, most notably R&D. Its importance lies in its direct positive impact on future innovation performance and competitiveness (Kostopoulos et al., 2011). By enabling SMEs to engage in R&D and innovation (which may not be possible without public assistance), public instruments enable knowledge accumulation, which in turn augments absorptive capacity and improves future performance.

Lastly, the data for this study was collected in Croatia, a developing economy. Studies examining the effects of R&D policies have focused mostly on developed economies while similar studies for developing countries are very scarce (Ozcelik and Taymaz, 2008). Our paper seeks to contribute to the filling of that gap.

This paper is organized as follows: section two presents the institutional background; section three contains the literature review; section four develops the hypotheses; section five introduces the methodology; section six elaborates on the data used in this paper; section seven presents the data analysis and results; section eight discusses the results and section nine concludes the paper.

2. Institutional background

Croatia has gone through an intense period of political, economic and social transition, and the system of R&D and innovation support has since been changing accordingly and adjusting to EU guidelines. The Government has always been the main investor in science and R&D, with the private sector contributing only about one third of the funds. Research and development have mainly been supported by tax incentives and subsidies.

Subsidies for R&D and innovation are provided through several institutions. One of these is the Business Innovation Center of Croatia or BICRO, which was founded by the Croatian Government in 1998 in order to implement technological development and innovation support programs. BICRO offers competitive matching grants aimed at SMEs. Other subsidy programs are provided through the Ministry of Economy, and the Croatian Agency for SMEs (HAMAG) which targets SMEs specifically. The funding conditions vary from program to program, but mostly funding takes place through matching grants. Innovation subsidy programs do not make any exclusion on eligibility based on the industrial sector; funding is based on the quality and creativity of the proposed industry projects.

Tax incentives for R&D were introduced into the Croatian tax system in 2003. They may be awarded for categories of fundamental research, industrial and development research, technical feasibility studies, and innovation. Enterprises are allowed to lower their profit tax base by 150 percent of the eligible cost for fundamental research, 125 percent of the eligible cost for industrial research, and 100 percent of the eligible cost for development research. The total amount of the aid awarded, based on all the possible grounds, cannot, however, be higher than 100 percent of the eligible cost for fundamental research, 50 percent of eligible cost for industrial research and 25 percent for development research. In the case of small enterprises these percentage points for industrial and development research can be increased by 20 percentage points, and in the case of medium-sized enterprises by 10 percentage points.

The goals of both subsidies and tax incentives can be summed up as increasing the competitiveness of the Croatian industry through enabling innovation. The policy makers do not have specific strategic goals that they wish to realize with these instruments, such as facilitating innovativeness in certain industries. This is most

Table 1
State aid for research and development and innovation in the period 2004–2009.
Source: Croatian Competition Agency, Annual Reports on state aid for years 2006, 2007, 2008, 2009.

	2004 In mil. EUR	2005 In mil. EUR	2006 In mil. EUR	2007 In mil. EUR	2008 In mil. EUR	2009 In mil. EUR
Grants	0.0	0.6	2.4	0.7	6.5	4.3
Tax advantages	16.5	16.8	16.6	21.3	22.5	14.6
Total	16.5	17.5	19.0	21.9	29.0	19.0
As % in horizontal aid	10.8	14.0	12.9	24.1	31.6	21.1
As % in total state aid (less agriculture and fisheries)	3.7	4.0	2.3	2.0	3.5	2.8
As % of total state aid	2.4	2.5	1.6	1.4	2.2	1.6
As % of GDP	0.06	0.06	0.06	0.05	0.06	0.04

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likely caused by the lack of consensus on general strategic priorities for the future development of the country. Instead, the instruments are geared toward increasing the innovation capability of the program recipients with the hope that in time, these new skills and capabilities will spread to the rest of the economy.

On the whole, the nominal value of state aid for R&D has increased since 2004, but its size in terms of total state aid and GDP has remained constant (Table 1). Due to interest from the business community, there is constant pressure from some grant-giving agencies to increase government investment in R&D programs. In the highly intensive competition for state funds these programs are not viewed as a priority despite general awareness of the need to increase the innovative capability of the Croatian industry. A possible cause for this is absence of systematic evaluation of these programs' results, which deprives program advocates of the arguments needed for proving the existence of a need for additional investment. The present study is one of the first attempts to evaluate the effectiveness of subsidy programs and tax incentives for R&D and innovation in Croatia.

3. Previous evidence

Both tax incentives and direct subsidies are aimed at correcting market failure. Direct subsidies are neutral with respect to the business tax structure and they usually focus on projects with a higher social rate of return: in this way they allow the government to retain control over the type of R&D and to promote desired objectives (Bérubé and Mohnen, 2009). While direct grants are given to individual firms for specific R&D projects, tax incentives are provided to encourage a large population of interested firms to engage in R&D. Tax incentives are neutral with respect to the choice of industry and the nature of the firm (Czarnitzki et al., 2011). Unlike direct grants, tax incentives do not allow for any governmental control over the use of the subsidy: private firms will use the credits to first fund the projects with the highest rate of private return (Hall and Van Reenen, 2000).

The existing literature mostly reports positive effects of public support schemes on R&D efforts in companies, although the evidence is not conclusive. Below we address each instrument separately.

3.1. The effects of direct R&D subsidies

The effects of direct subsidies can be better measured than those of fiscal indirect support (Bérubé and Mohnen, 2009). Regarding the effect of subsidies, one of the longstanding questions is whether firms substitute subsidy for their own R&D investment (this is usually referred to as *crowding out*). Although recent studies tend to reject full crowding-out effects, the results are ambiguous: Aerts and Czarnitzki (2006; 2004), Almus and Czarnitzki (2003), Czarnitzki (2001), Czarnitzki and Fier (2002), Duguet (2004), Fier (2002), Gonzalez and Pazo (2006), Gonzalez et al. (2005), Gorg and Strobl (2007), Hussinger (2008), Loof and Heshmati (2005), Reinkowski et al. (2010), and Herrera and Sánchez-González (2013) reject full crowding-out effects, while Busom (2000), Heijs and Herrera (2004), Kaiser (2004), Lach (2002), Suetens (2002), and Wallsten (2000) find indications that public R&D funding replaces private R&D investments to some extent.

Recently it has been recognized that subsidies may initiate other important changes in firms' behavior and output. Czarnitzki and Licht (2006) and Czarnitzki and Fier (2002) find that firms which receive direct R&D subsidies spend more on innovation and R&D, and that direct subsidies influence firms' patenting activities in a positive way (Czarnitzki and Licht, 2006). Clausen (2009) empirically shows that research subsidies stimulate R&D spending within firms while development subsidies substitute such spending. According to Herrera and Sánchez-González (2013), subsidies increase innovation output, but the effect depends on firm size. Czarnitzki and Lopes-Bento (2011) find that direct grants increase the number of innovations, and Hottenrott and Lopes-Bento (2014) show that targeted R&D subsidies increase sales generated from novelties.

As for the impact on firms' behavior, Buisseret et al. (1995) specify that subsidies can have an effect on the breadth of innovation activities and can lead to changes in both the technological and business strategies of the firm in question. Very few studies (such as Clarysse et al., 2009 and Hsu et al., 2009) provide empirical analysis of this issue. Impact on absorptive capacity was not investigated.

3.2. The effects of tax incentives

Most studies show that tax incentives cause increased R&D expenditure in firms (Czarnitzki et al., 2011; Baghana and Mohnen, 2009; Bloom et al., 2002; Hall and Van Reenen, 2000; Mamuneas and Ishaq Nadiri 1996; Kobayashi, 2014). Unlike studies on the effect of tax incentives on the firms' own R&D investments, microeconomic studies regarding the effect of tax credits on firms' performance and innovation are scarce. Czarnitzki et al. (2011) analyze the impact of R&D tax credits on the innovation activities of Canadian firms and show that recipients attain a higher number of product innovations, as well as report an increase in sales of new and improved products. However, the authors find the effect on firm performance lacking, although they posit that this effect may become evident in time. Bérubé and Mohnen (2009) also find that R&D tax incentives have a positive impact on innovation in recipient firms. They observe that firms using both R&D grants and R&D tax credits are more innovative than those using tax incentives only. Cappelen et al. (2012) study the effects of the Norwegian tax scheme on the likelihood of innovation and patenting, and do not find positive effects. Hanel (2003) finds that firms using R&D tax credits in Canada are more likely to introduce the most original world-first innovations than other firms. To the authors' knowledge, the effect of tax incentives on changes in absorptive capacity or firm behavior has not been studied.

3.3. Studies addressing joint use of subsidies and tax incentives

While a significant body of work addresses the effectiveness of one of these instruments, there are very few studies on their joint effectiveness. Bérubé and Mohnen (2009) compare the effects of subsidies and tax incentives on the same set of firms, and find that using both tax incentives and subsidies improves innovative output more effectively than the use of tax incentives alone. The firms in the quoted study preferred tax incentives (the study was not focused on SMEs as the sample contained firms of all sizes). Busom et al. (2014) examined the use of tax incentives and subsidies in addressing two sources of market failure, namely financing constraints and problems with appropriability. They find that financially constrained SMEs are more likely to use subsidies than tax incentives, while SMEs that utilize legal intellectual protection methods prefer tax incentives. Busom et al. (2014) conclude that these two instruments have different abilities when it comes to addressing the causes of market failure, and can actually be used as complements in the policy sense.

4. Hypotheses development

Although both tax incentives and direct subsidies are envisioned as instruments for market failure correction, they differ on

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Table 2
Comparison between tax incentives and subsidies.

	Tax incentives	Subsidies
Timing	Obtainable ex post: firm uses available funds and gets tax relief later	Obtainable upfront (at least partly): funds are available before the project begins
Eligibility/ requirements	Easy to claim (every firm files taxes at the year's end) Any R&D project is eligible May encourage projects with larger private returns	Involves effort to write the project application Only projects satisfying agency requirements are eligible Mostly used for encouraging projects without private returns, but with larger public benefits
Magnitude	The amount of support depends on the firm's tax position (may be difficult to predict for SMEs)	Firms knows the exact amount of the support for the accepted project

a variety of points. Following Busom et al. (2014), these differences can be summarized in three groups: timing of support, eligibility/requirements for support, and magnitude of support (Table 2).

In this paper we address the ability of public instruments to affect R&D intensity, capacity, and innovative output, but we also go one step further to examine their effect on certain crucial capabilities of the firm.

Firms constantly reconfigure their resources and capabilities in order to overcome competitive weaknesses, and innovation is a crucial instrument in this reconfiguration (Hewitt-Dundas, 2006). Through innovation, the firm's base of codified, firm-specific and tacit knowledge builds up: this enables the creative accumulation of knowledge and competencies (Malerba et al., 1997). Both tax incentives and direct grants make it possible for firms to engage in new projects and to consequently accumulate knowledge through experience. This higher level of accumulated competencies will significantly affect the future technological performance of the firm (Hewitt-Dundas, 2006). So we postulate that participation in a public program goes beyond just affecting R&D input (which has been the focus of most existing literature) and innovation output (which has recently been addressed in the literature) to reach some of the crucial capabilities of the firm. By eliciting change in these capabilities, public instruments can have a profound effect on the firm and can shape future firm performance. A particular capability that we explore in this paper is absorptive capacity.

4.1. *Impact on R&D intensity and capacity*

Most studies discussed in the literature review show that public instruments increase R&D expenditures to some degree, although this evidence is not conclusive. In this paper we focus on R&D intensity (measured as the share of R&D expenditures in turnover) because it is a better indicator of the extent of the importance of R&D for a firm and the extent of its orientation toward R&D. Most studies which find positive effects on R&D intensity are performed on a sample of firms of all sizes, but some studies confirm positive effects for SMEs as well (Hottenrott and Lopes-Bento, 2014; Reinkowski et al., 2010; Herrera et al., 2010). A related aspect that we investigate is the capacity of a firm to conduct R&D as measured by R&D employment.

Increasing R&D intensity and capacity is an important issue for SMEs because they are known to generally under invest in R&D due to the "lack of knowledge about how and where to acquire necessary competences" (Ortega-Argiles et al., 2009). We postulate that participation in both direct grants and tax incentives will cause positive changes in R&D intensity and employment in SMEs. Another expected change is that by engaging more intensely in R&D the companies will change their R&D-related behavior. For example, they will learn their way around the "knowledge market", and consequentially will tend to collaborate more with the knowledge centers such as research institutions.

Hypothesis 1A. Compared to no treatment, receiving a direct subsidy (alone or together with tax incentive) has a positive impact on R&D intensity, and the number of R&D employees.

Hypothesis 1B. Compared to no treatment, receiving a direct subsidy (alone or together with tax incentive) has a positive impact on R&D collaboration with research institutions.

4.2. *Impact on innovation output*

One of the main objectives of R&D instruments is to induce firms to innovate through reducing the cost of R&D. There is still considerable uncertainty as to the effect of public programs on economic returns from innovation activity (Herrera and Sánchez-González, 2013), and studies addressing this topic are scarce (Czarnitzki et al., 2011). Recently a few studies have started examining the effect of public programs on innovation output: Czarnitzki et al. (2011) find positive impact of tax incentives on the number and sales of new products, and Herrera and Sánchez-González (2013), Czarnitzki and Lopes-Bento (2011), and Hottenrott and Lopes-Bento (2014) show that direct grants increase innovative output. Bérubé and Mohnen (2009) find that firms which receive direct grants in addition to R&D tax incentives improve their innovation performance compared to those which receive only R&D tax incentives.

In the case of SMEs, their limited resources may prevent them from innovating. By lowering the cost of R&D, the public instrument can make it possible for an SME to carry out a project which might have been judged as too expensive.

Hypothesis 2. Compared to no treatment, receiving a direct subsidy (alone or together with tax incentive) has a positive impact on the number of innovations and the overall share of innovation in income.

4.3. *Impact on absorptive capacity*

Studies on absorptive capacity in SMEs seldom appear in literature. In this paper we follow the conceptualization of absorptive capacity offered by Zahra and George (2002), who recognize four aspects of absorptive capacity: knowledge acquisition, assimilation, transformation, and exploitation. Zahra and George (2002) define these dimensions as follows: acquisition refers to the firm's capability to identify and acquire externally generated knowledge that is critical to its operations. Assimilation refers to a firm's routines and processes that allow it to analyze a process, interpret, and understand the information obtained from external sources. Transformation denotes a firm's capability to develop and refine the routines that facilitate combining existing knowledge and the newly acquired and assimilated knowledge. Exploitation is an organizational capability which is based on the routines that allow a firm to refine, extend, and

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leverage existing competencies or to create new ones by incorporating acquired and transformed knowledge into its operations.

It has been shown that experience influences the development of a firm's absorptive capacity (Zahra and George, 2002). Inadequate resources often prevent SMEs from innovating at the desired level, which thwarts knowledge accumulation and inhibits the increase of absorptive capacity that would naturally occur through this experience. Therefore, we expect that by enabling SMEs to engage in R&D and innovation, public instruments will facilitate the build-up of absorptive capacity.

Hypothesis 3. Compared to no treatment, receiving a direct subsidy (alone or together with tax incentive) has a positive impact on the acquisition, absorption, transformation and exploitation aspect of absorptive capacity.

4.4. Comparison of different instruments

Although tax incentives and direct subsidies are both intended to correct market failure, they differ on several key points and as such address causes of market failure in different ways (Busom et al., 2014). Tax credits are a very convenient instrument for companies as they are easy to claim, and no requirements are imposed on the eligibility of the project. However, for SMEs, subsidies may be more significant than tax incentives for several reasons. First, financially constrained SMEs lack funds to invest in the project upfront. Only those companies that are able to invest in advance using either own finances or some other private funding can benefit from tax incentives. Even so an SME's investment (and thus the tax credit) is most likely not going to be adequate for a larger project. Second, the amount of support may depend on the firm's taxable income at the end of the tax year, which for SMEs may be difficult to predict (see Busom et al., 2014). Third, SMEs are less likely to practice formal intellectual property protection (Leiponen and Byma, 2009), which exposes their innovation results to ready imitation by competitors. As a result, SMEs may be reluctant to use private resources to fund R&D activities when the threat of competitor imitation may impede a return on their investment. All these reasons point to subsidies as the more appropriate instrument for SMEs.

Having elaborated on the relative disadvantages of tax incentives for SMEs, it needs to be recognized that benefiting from a subsidy is not without its cost. It involves time and skilled labor to prepare a good proposal. If the proposal is awarded, the firm may have to undergo periodic evaluations and review from the grant giving agency during the project execution, and is required to comply with specific accounting standards. However these obstacles may be easier to work around than the financial and appropriability constraints. For example, employees may work on the proposal preparation after work hours, thus investing their time to attract the money that the firm needs.

For these reasons we can expect that in SMEs which use both instruments, the role of tax incentive is more of a type of fill-in support for imitative or other less demanding projects, while large projects which require considerable investments that are difficult to recoup are financed by subsidies. In this sense the two instruments act as complements on the project portfolio level within the same company. This is a micro-level reflection of the policy complementarity showed in Busom et al. (2014), namely that subsidies encourage risky or first time R&D in new R&D performers while tax incentives are suitable for stable R&D performers.

Since we can expect subsidies to be the main instrument for SMEs, the question is whether adding tax incentives on top of subsidies would have any significant effect on R&D, innovation and absorptive capacity. One can easily argue that, since on average, tax incentives do not seem that important for SMEs, the additional benefit that they offer is not likely to be significant compared to the benefit of using subsidies only. However, although in SMEs tax incentives are more likely to be used for less risky and maybe less innovative projects, they still enable the firm to perform more R&D. This consequently affects the basic capabilities of the firm, and as such should produce some effect. Therefore we postulate that in general adding tax incentives on top of subsidies will improve R&D, innovation output and absorptive capacity.

Hypothesis 4. Compared to the use of subsidies alone, using tax incentives together with subsidies has a positive impact on the following:

(a) R&D intensity and the number of R&D employees.
(b) R&D collaboration with research institutions.
(c) The number of innovations and the share of innovation in income.
(d) The acquisition, absorption, transformation and exploitation aspect of absorptive capacity.

5. Methodology

The question that we seek to answer in this paper is what would have happened with the firms that used public instruments for R&D&I if they had not used them (i.e. we seek to compare the real-world outcome with a counterfactual scenario). The problem with economic policy interventions is that companies are not randomly assigned to the treatment condition but instead they choose to apply, which introduces selection bias in the observational data. Consequently, we cannot use the average outcome on all non-recipients to estimate the counterfactual effect. This problem was addressed by Rubin (1977) who introduced the conditional independence assumption (CIA). The CIA states that potential outcomes are independent of treatment assignment given a set of observable covariates X which are not affected by the treatment. This implies that selection is based on observable characteristics that can be observed by the researcher. Practically CIA allows researchers to employ matching methods to pair participants with nonparticipants which are as similar as possible on pre-treatment characteristics, and use the latter group to estimate the counterfactual scenario.

As exact matching on each covariate is not possible when dealing with a large number of covariates, methods have been found to summarize this information into one scalar. The most popular among these methods are the propensity score and Mahalanobis distance methods (Stuart and Rubin, 2007).

Propensity score: Rosenbaum and Rubin (1983) define the propensity score $p(X)$ as the conditional probability of receiving a treatment given a vector of covariates X. We assume that after conditioning on these variables, the expected outcome in the absence of treatment does not depend on treatment status. If by $D=\{0, 1\}$ we denote the indicator of exposure to treatment, then $p(X)=P(D=1|X)=E(D|X)$. For a firm i, the propensity score can be estimated using any standard probability model in the following way: $P(X_i)=P(D_i=1|X_i)=F\{h(X_i)\}$, where $F(.)$ is the normal or the logistic cumulative distribution and $h(X_i)$ is a function of covariates which can contain linear and higher order terms. Propensity scores are usually restricted to the area of common support, which means that we consider only those observations which belong to the intersection of the intervals of propensity scores for treated and control observations. Common support is used to improve the quality of the matching.

Mahalanobis metric: The Mahalanobis metric measures dissimilarity between observations based on the vector of covariates X. The Mahalanobis distance between respondents i and j is

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defined by the formula $D_{ij} = (X_i - X_j)'\Sigma^{-1}(X_i - X_j)$, where X is the vector of covariates and Σ is the variance-covariance matrix of X in the control sample. The Mahalanobis distance is used for matching, where for each treated unit one or several non-treated units are found that have the smallest distance measured by the Mahalanobis metric. One can calculate just the distances between propensity scores (in which case the Mahalanobis metric becomes just the Euclidian metric), or we can use propensity scores as well as a set of covariates, as is done in this paper.

Matching has the advantage that no requirements are made on the functional form or the error terms, but it also has the disadvantage that it only controls for the selection on observables. In other words, we assume that the covariates in the model completely determine the selection into treatment. Since this is a limitation of the matching approach, in this paper we also perform IV regression to check the robustness of our results.

Propensity matching and Mahalanobis matching perform similarly when the number of covariates is small. When the number of covariates is large propensity score matching is more suitable; the Mahalanobis distance works quite well when the number of covariates is fewer than eight, and when the sample is small (Zhao, 2004). For these reasons it was proposed in literature to combine these two methods, in particular when there are some covariates for which particularly close matches are required (Rubin and Thomas, 2000). In this paper we use a combination of the two methods because a relatively large number of covariates in our study would suggest the use of propensity methods, while our relatively small sample would benefit from the use of Mahalanobis matching.

5.1. Comparison of treatments

The matching algorithm (using propensity score alone or jointly with other covariates) has been used extensively in estimation of the effects of R&D subsidies and was employed in studies by Almus and Czarnitzki (2003), Duguet (2004), Aerts and Czarnitzki (2006, 2004), Reinkowski et al. (2010), Herrera et al. (2010), Czarnitzki et al. (2011), Czarnitzki and Lopes-Bento (2013), and Herrera and Sánchez-González (2013) among others.

In all the quoted studies the treatment is dichotomous: the firm either used an instrument or not. Because in our case we have two types of R&D instruments, in general we have four possible alternatives. More precisely: there are firms that received subsidies only, those that received tax incentives only, those that received both, and those that received nothing.

To model this situation Lechner (1999) proposes a multilevel matching procedure which is a generalization of propensity score matching. This approach allows for involving multiple mutually exclusive treatments, where propensities for selection into multiple treatments are modeled using multinomial logit or probit. A practical alternative to the use of multinomial logit or probit is to estimate a series of binomial models as suggested by Lechner (2001). According to Lechner (2001), a comparison of relative performance of the multinomial probit approach and serial estimation approach shows little difference. Serial estimation approach may even be more robust since a mis-specification in one of the series will not compromise all the others as is the case with the multinomial probit model (Caliendo and Kopeinig, 2008).

Since in this paper we deal with two instruments, the use of which can be correlated, instead of multinomial approach or serial estimation we will use a seemingly unrelated bivariate probit. We specify the seemingly unrelated probit where the two dependent variables are as follows: $y_1 = 1$ if a tax incentive was received, and $y_2 = 1$ if a subsidy was received. More precisely,

$$y_1^* = x_1'\beta_1 + \varepsilon_1, y_1 = 1 \text{ if } y_1^* > 0, 0 \text{ otherwise}$$

$$y_2^* = x_2'\beta_2 + \varepsilon_2, y_2 = 1 \text{ if } y_2^* > 0, 0 \text{ otherwise}$$

here y_1^*, y_2^* are latent variables underlying the binary variables y_1, y_2, and the disturbances $\varepsilon_{1,}, \varepsilon_2$ are normally distributed with mean 0 and variance 1. The correlation between the disturbances is denoted as $Cov(\varepsilon_1, \varepsilon_2 | x_1, x_2) = \rho$. Seemingly unrelated probit allows for different vectors of the independent variables x_i to determine the outputs y_i (the special case when $x_1 = x_2$ becomes bivariate probit).

By means of a seemingly unrelated bivariate probit we obtain four predicted joint probabilities for each observation: $P(1,1|X)$, $P(0,1|X)$, $P(1,0|X)$ and $P(0,0|X)$. These are the probabilities of receiving a specific combination of public instruments conditional on the pretreatment characteristics X. Compared to the serial approach, the predicted probabilities that we use as matching criteria are more comparable. Since we are not aware of any other studies that used matching procedure based on bivariate probit, in the Appendix we provide proof that Lechner's (1999) procedure remains valid if we replace the multinomial logit/probit with a seemingly unrelated bivariate probit.

5.2. Matching algorithm

In this paper we adapt the approach used in Lechner (2002) and Czarnitzki et al. (2011) who combined the propensity matching and Mahalanobis matching in the following way: in step 1 the propensity score is computed, and in step 2 the Mahalanobis matching on the basis of the computed propensity scores and several chosen covariates is performed. In this paper we adapt the first stage by estimating the conditional probabilities stemming from the seemingly unrelated bivariate probit. More precisely:

Step 0: Choice of alternatives for comparison
We select a pairing of different alternatives to compare, one of them represents treated observations and the other consists of control observations. (For example, we compare firms that received only subsidies with those that did not use any instrument.)
Step 1: Propensity score computation
We estimate seemingly unrelated bivariate probit on the full set of covariates X. We compute conditional probability of being in treatment based on all observations, and then retain only those observations belonging to the specific treatment and control chosen in step 0. Next we determine the common support as the intersection of the intervals of conditional probability for treated and control observations. (In the above example of comparing firms that received only subsidies with those that did not use any instrument, we compute the conditional probability $p = P(0,1|X)$ for each observation and retain only those observations that correspond to the two alternatives under consideration, i.e. the alternatives "subsidies only" and "no participation". We determine common support as the intersection of the intervals of the propensity scores for those two groups of firms.)
Step 2: Mahalanobis matching with the propensity score included
Mahalanobis matching is performed on the common support determined in step 1. In addition to the probability p computed in step 1, we choose a smaller number of selected covariates $X_1, X_2, \ldots, X_n$ so that the distance is computed based on $X_1, X_2, \ldots, X_n, p$. We use the nearest neighbor matching, where we take a treated unit and choose the closest non-treated unit as its match (i.e. the unit with the minimal Mahalanobis distance from the treated observation). Mahalanobis matching is done with replacement, which means that once a control

observation is used as a match, it is not deleted from the set of controls and can thus be reused.

For an outcome variable Y, the average effect on the treated (or ATT) can be estimated in the following way: $ATT = \frac{1}{N^T}\sum_{i \in T}\left(Y_i^T - Y_i^C\right)$ where the sum goes over all the treated units and N^T is the number of treated units. For the treated unit i, Y_i^T stands for the value of the outcome variable Y, while Y_i^C denotes the value of the outcome variable for the nearest neighbor of the treated unit i. Analytical standard errors are computed using Abadie–Imbens formula (Abadie and Imbens, 2006), which takes replacement into account. The matching is performed using Stata package PSMATCH2 by Leuven and Sianesi (2003).

To assess the quality of the matching, we need to check that the pre-treatment variables are balanced between the treated and the control subjects (Rosenbaum and Rubin, 1983). For each covariate X the mean is computed for treated and control subjects after matching, and these means are compared. If they do not differ significantly, then the balancing property holds. With balancing property satisfied, exposure to treatment can be considered random.

Since the use of tax incentives only is not the focus of our paper, and since only a small fragment of the sample belongs to this group (6 firms), we will not perform matching for this group.

6. Data

The data for this study comes from a survey performed in 2010 on a sample of 700 SMEs in Croatia. The period under investigation during which a firm could have used a public grant or a tax break is the time period between 2005 and 2010. The database was constructed based on the recipients of public programs for R&D according to information from grant-giving agencies and the Croatian Ministry of Finance. It was further supplemented by the SME competitors of the recipient firms according to the NACE code; this information was obtained from the business register of all Croatian enterprises. Both service and manufacturing firms were included. Out of the 700 companies, 225 enterprises responded, which constitutes a response rate of 33 percent.

The survey instrument used in this study was a highly structured questionnaire involving the use of binary (yes–no) questions, choice questions, and Lickert scales. The questionnaire was web-based and addressed to the directors/owners of the companies. The respondents were asked to provide some economic data and answer questions regarding their R&D/innovation capability and participation in public subsidy programs. In order to obtain a high response rate, telephone follow-ups were used.

In order to ensure that the conditional independence assumption is satisfied, we supplemented the survey data with balance sheet data stemming from the Croatian Financial Agency dataset. This data relates to the year 2005, which is the beginning of the period for which the use of public instruments is investigated. Since not all companies provided this financial data, our final sample was reduced to 175 firms.

6.1. Variables for matching

6.1.1. Treatment variables

In order to measure the effect of subsidies and tax incentives, two treatment variables were defined, *Subsidies only* and *Tax incentives and subsidies,* as well as a control group consisting of untreated observations, labeled *No treatment* (Table 3). These variables and the control group define three disjoint sets of firms.

6.1.2. Covariates

The covariates for propensity matching are defined in Table 4. To avoid simultaneity, covariates in the first-stage model should be either (1) measured at the beginning of the period in question, (2) deterministic with respect to time (e.g. age), or (3) constant throughout this period.

Covariates measured at the beginning of the period (in 2005): these are the variables *Develop, Lnsize, Lnexp, Lnsalestot, Lnprofit* and *Nonmat*. The size of the firm, both in terms of the number of employees and the total sales is shown in other studies to be related to the probability of using state aid. The same is true for exporters. The variable *Develop* indicates the existence of development activities in the firm, which makes it more likely to use both grants and tax incentives. The variable *Nonmat* shows the percentage of non-material assets in total sales. Since these assets include patents, licenses, development projects etc., we use it as a proxy for the knowledge capital of the firm. It is conceivable that firms with larger knowledge capital are more likely to avail themselves of the incentives for R&D&I.

Covariates deterministic with respect to time: this is the variable *Lnage*.

Covariates constant throughout the period from 2005 to 2010: these are the industry sector variables *High-tech, Medium high-tech, Medium low-tech, Low-tech,* and *KIS*, and the variable *R&D orientation*. Since industry sector variables have large inertia, we assume that these variables were constant from 2005 to 2010. To define these variables, we divide companies into a manufacturing group and a services group, and within each group we differentiate them according to the level of knowledge or technology required.

The variable *R&D orientation* is a proxy for the existence of certain resources and capabilities related to R&D and innovation that were present in the entire 2005–2010 period. We argue for this assumption on the grounds that these resources and capabilities take a long time to develop, are present in a company even before they become embodied in a specific outcome, and persist over time. We use this variable to indicate deeper orientation toward R&D: this is particularly true of SMEs because they are known to be able to innovate without formal R&D. We consider this R&D orientation to be persistent throughout the 2005–2010 period. If the firm had an R&D department in 2005, the R&D orientation is clear. However, we have to address the case in which the firm has created a formal R&D department after 2005 (i.e. during the period in question). We can argue that there is large organizational inertia involved in setting up a formal R&D department. Even if the department did not exist as a formal entity in 2005, the firm must have had an intrinsic drive to develop in this direction. It must have started accumulating knowledge, resources and

Table 3
Treatment variables (all variables refer to the time period 2005–2010).

Variable name	Description
Subsidies only	1 if the firm received only a direct grant for R&D (i.e. it did not receive a tax incentive as well), 0 otherwise
Tax incentives and subsidies	1 if the firm received both a subsidy and a tax incentive for R&D, 0 otherwise
No treatment	1 if the firm received neither a subsidy nor a tax incentive for R&D, 0 otherwise

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Table 4
Covariates for estimation of propensity scores.

Variable name	Description
R&D orientation	Measured by existence of formal R&D department in 2005-2010: 1 yes, 0 no
Develop	Indicates whether in 2005 the firm reported having spent resources for development projects: 1, if yes, 0 if no
Lnage	The logarithm of the firm's age
Lnsize	Logarithm of the number of employees in 2005, i.e. ln(number of employees+1)
Lnsize2	The square of *Lnsize*
Lnexp	Logarithm of the exports in 2005 (more precisely, ln(exports+1))
Lnsalestot	Logarithm of the total sales in 2005
Nonmat	Percentage of non-material assets in total sales measured in 2005 (these include revenues from patents, licenses, development projects, etc. and we use it as a proxy for knowledge capital of the firm)
Lnprofit	Logarithm of the profit in 2005 (more precisely, ln(profit+1))
*Lnage *R&D*	The interaction of *Lnage* and *R&D orientation*
*Lnsize*R&D*	The interaction of *Lnsize* and *R&D orientation*
*Lnage*Lnsize*	The interaction of *Lnage* and *Lnsize*
*Nonmat*R&D*	The interaction of *Nonmat* and *R&D orientation*
*Lnexp*R&D*	The interaction of *Lnexp* and *R&D orientation*
High-tech	Belonging to high technology manufacturing sector according to NACE Rev.2: 1 yes, 0 no
Medium high-tech	Belonging to medium high technology manufacturing sector according to NACE Rev.2: 1 yes, 0 no
Medium low-tech	Belonging to medium low technology manufacturing sector according to NACE Rev.2: 1 yes, 0 no
Low-tech	Belonging to low technology manufacturing sector according to NACE Rev.2: 1 yes, 0 no
KIS	Knowledge intensive service according to NACE Rev.2: 1 yes, 0 no

Table 5
Output variables.

Variable name	Description
R&D intensity	R&D intensity reported in 2010
Number of employees in R&D	Number of employees classified as R&D in 2010
RI collaboration	1 if the company collaborated with a research institution in 2008-2010, 0 otherwise
Number of innovations	Number of innovations introduced in time period 2008-2010
Percentage of sales from innovation	Percentage of income from sales of products and services in 2010 that is derived from innovations developed in the period 2008–2010
*Absorptive capacity—acquisition***	Index computed from these three items*: – The search for relevant information concerning our industry is every-day business in our company. – Our management motivates the employees to use information sources within our industry. – Our management expects that the employees deal with information beyond our industry. – (Cronbach alpha 0.76, inter-item correlation 0.52)
*Absorptive capacity—assimilation***	Index computed from these four items: – In our company ideas and concepts are communicated cross-departmental. – Our management emphasizes cross-departmental support to solve problems. – In our company there is a quick information flow, e.g., if a business unit obtains important information it communicates this information promptly to all other business units or departments. – Our management demands periodical cross-departmental meetings to interchange new developments, problems, and achievements. – (Cronbach alpha 0.9, inter-item correlation 0.71).
*Absorptive capacity—transformation***	Index computed from these four items: – Our employees have the ability to structure and to use collected knowledge. – Our employees are used to absorb new knowledge as well as to prepare it for further purposes and to make it available. – Our employees successfully link existing knowledge with new insights. – Our employees are able to apply new knowledge in their practical work. (Cronbach alpha 0.95, inter-item correlation 0.84)
*Absorptive capacity—exploitation***	Index computed from these three items: – Our management supports the development of prototypes. – Our company regularly reconsiders technologies and adapts them accordant to new knowledge. – Our company has the ability to work more effectively by adopting new technologies. (Cronbach alpha 0.86, inter-item correlation 0.68)

* The items in all four dimensions of absorptive capacity were measured on the scale from 1 (totally disagree) to 7 (totally agree).
** Questions are asked for 2010.

capabilities for R&D that were later employed in a formal setting. In other words, the R&D orientation was present even before the formal set-up, as well as afterwards. Therefore we may argue that this variable indeed measures the existence of a deeper dedication to R&D which persisted during the period in question, and in this sense we can justify using it as a covariate.

In the model we also use a number of interactions that are relevant in this situation. Higher order terms and interactions in the propensity score specification can improve the matching (Caliendo and Kopeining, 2008), so we include selected variables of this type in our model. We consider (1) the interactions between firm size, age, exports, and non-material assets on one

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side and R&D orientation on the other, and (2) the interaction between firm age and size. In addition to improvements in matching, these interactions allow us to capture deeper relationships between variables. For example, firm size may be negatively related to subsidies (i.e. larger firms may prefer tax incentives), but this effect may be diminished if the firm has an R&D department as the permanent R&D staff has the capacity to apply for subsidies as well. The effect of a variable may also be amplified by the existence of an R&D department: for example the firms that own non-material assets and have permanent R&D staff may be more likely to use public instruments than those which own non-material assets without any supporting organizational structure.

6.1.3. *Output variables*

We measure the effects of direct subsidies or tax incentives on R&D intensity and capacity, the number of innovations, the percentage of sales from innovations, and various aspects of absorptive capacity. All output variables are listed in Table 5.

Although in the past absorptive capacity was measured by R&D proxies, Flatten et al. (2011) point out that this approach does not adequately capture the concept. Instead, Flatten et al. (2011) develop a scale that measures all four aspects of the absorptive capacity defined by Zahra and George (2002): this scale is adopted in this paper. The scale generates four variables that are computed as indexes which are composed of three or four items (items are specified in Table 5). The indexes show good reliability and inter-item correlations.

6.2. *Descriptive statistics*

After having defined both covariates and output variables, we present some basic information on the companies in the sample. There are 39 firms that used subsidies only, 21 firms that used both instruments, and 115 firms that did not use any instrument, (6 firms that used tax incentives only are excluded from further analysis). Table 6 presents the descriptive statistics for each of the groups. It reports the values of the covariates and output variables for each of the groups, and reports the significance of comparison using the *t* test.

We can see that when compared to the firms that underwent no treatment, those SMEs that participated in public programs tend to be more R&D oriented. In addition, the firms that used both instruments were also more profitable with larger non-material assets compared to those that did not participate in any program. As for the outcomes of the public schemes, the data shows significant improvements in both R&D and innovation output for recipients compared to non-recipients. The comparison between firms that used both instruments compared to subsidies only showed almost no significant differences.

Table 6
Dependent variables and output variables, mean comparison between groups before matching (2-tailed *t*-test).

	Subsidies only vs. *No treatment* ($n=154$)		*Tax incentives and subsidies* vs. *No treatment* ($n=136$)		*Tax incentives and subsidies* vs. *Subsidies only* ($n=60$)	
	Treated $N=39$	Control $N=115$	Treated $N=21$	Control $N=115$	Treated $N=21$	Control[a] $N=39$
Covariates						
R&D orientation	0.283;***	0.09	0.383;***	0.09	0.38	0.28
Develop	0.10	0.03	0.05	0.03	0.05	0.10
Lnage	2.77	2.85	2.89	2.85	2.89	2.77
Lnsize	2.53	2.63	2.96	2.63	2.96	2.53
Lnsize2	8.86	8.38	10.46	8.38	10.46	8.86
Lnexp	0.192;**	0.09	0.09	0.09	0.09	1.19
Lnsalestot	14.11	15.08	15.81	15.08	15.81	14.11
Nonmat	0.35	0.96	3.722;**	0.96	3.722;**	0.35
Lnprofit	0.05	0.05	0.082;**	0.05	0.081;*	0.05
*Lnage 1;*R&D*	0.823;***	0.25	1.173;***	0.25	1.17	0.82
*Lnage1;*Lnsize*	7.54	7.68	8.97	7.68	8.97	7.54
Lnsize1; R&D*	1.013;***	0.28	1.263;***	0.28	1.26	1.01
*Nonmat1;*R&D*	0.05	0.41	0.17	0.41	0.17	0.05
*Lnexp1;*R&D*	0.04	0.02	0.04	0.02	0.04	0.04
High-tech	0.23[b]	0.13	0.09	0.13	0.09	0.23
Medium high-tech	0.21	0.19	0.24	0.19	0.24	0.21
Medium low-tech	0.15	0.11	0.05	0.11	0.05	0.15
Low-tech	0.08	0.08	0.05	0.08	0.05	0.08
KIS	0.262;**	0.44	0.52	0.44	0.522;**	0.26
Output variables						
Number of employees in R&D	2.612;**	1.06	5.293;***	1.06	5.29*	2.61
R&D intensity	16.182;**	5.94	19.673;***	5.94	19.67	16.18
RI collaboration	0.463;***	0.12	0.623;***	0.12	0.62	0.46
Number of innovations	3.852;**	1.63	3.92*	1.63	3.92	3.85
Percentage of sales from innovation	23.462;**	9.08	24.333;***	9.08	24.33	23.46
Absorptive capacity—acquisition	5.60	5.57	6.02*	5.57	6.02	5.60
Absorptive capacity – assimilation	5.78	5.53	5.96*	5.53	5.96	5.78
Absorptive capacity—transformation	5.60	5.32	5.792;**	5.32	5.79	5.60
Absorptive capacity—exploitation	5.922;**	5.25	6.133;***	5.25	6.13	5.92

* Indicates significance up to 10%.
** Up to 5%.
*** Up to 1%.
[a] In this model treated refers to the firms that received both subsidies and tax incentives, and control refers to those that received subsidies only.
[b] This number means that 23% of the treated are high-tech firms.

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7. Data analysis

7.1. Propensity matching

We estimate ATT effects by isolating two by two treatment categories. This brings us to the estimation of three separate models: (1) subsidies only vs. no treatment, (2) both tax incentives and subsidies vs. no treatment, and (3) both tax incentives and subsidies vs. subsidies only. We use seemingly unrelated probit to compute propensity scores. Table 7 shows the results of seemingly unrelated probit estimation.

Since Table 7 shows that ρ is significantly different from zero, this implies that there is a relationship between the dependent variables which is caused by unobservable characteristics which are common to both error terms.

Table 7
Results of seemingly unrelated probit estimation.

	y_1 = *Tax incentives* N=181		y_2 = *Subsidies* N=181	
	Coeff.	St.err.	Coeff.	St.err.
R&D orientation	−9.31**	4.41	1.22	2.55
Develop	−0.02	1.54	0.77	0.58
Lnage	−1.12	1.01	−1.09*	0.65
Lnsize	−1.08	0.71	−1.18**	0.48
Lnsize2	−0.05	0.11	−0.02	0.07
Lnexp	−0.43	0.89	1.61**	0.63
Lnsalestot	0.22	0.15	0.02	0.06
Nonmat	0.13*	0.07	0.08**	0.04
Lnprofit	3.30	2.32	2.04	1.81
*Lnage *R&D*	3.73**	1.58	−0.38	0.98
*Lnage*Lnsize*	0.38	0.30	0.34*	0.18
*Lnsize*R&D*	0.04	0.40	0.52*	0.29
*Nonmat*R&D*	−0.41	0.26	−0.43**	0.19
*Lnexp*R&D*	−4.57*	2.46	−2.58	1.74
High-tech	0.27	0.70	−0.39	0.59
Medium high-tech	1.15*	0.67	−0.65	0.59
Medium low-tech	−0.60	0.84	−0.81	0.62
Low-tech[a]			−0.45*	0.64
KIS	0.75	0.63	−1.09	0.58
Constant	−2.24	3.39	3.09**	1.50
Atanh ρ	Coef.=1.29, Std. err.=0.39			
ρ	Coef.=0.86, Std. err=0.10			
ρ diagnostics	chi2(1)=25.58 Prob > chi2=0.00			
	Wald chi2(37)=59.94			
	Log likelihood=−129.14			
	Prob > chi2=0.01			

[a] Variable Low-tech perfectly predicts $y_1 = 0$ and is therefore omitted from the first equation.

7.2. Estimation of treatment effects

Having estimated the propensity scores, we can determine the common support and proceed to step 2 of the algorithm where the Mahalanobis matching is carried out. Matching is performed on the following variables: propensity score p, and the covariates *R&D orientation, Develop, Lnage, Lnsize, Lnexp, Nonmat,* and *Lnprofit.* To capture the effect of a higher level of knowledge or technology used in the company, the covariate *Techknow* is added to improve matching. This dummy variable is defined as 1 if the company belongs to either one of the following: high-tech manufacturing, medium high-tech manufacturing, or KIS.

After drawing up matches, we need to address the quality of the matching by verifying balancing property. Table 8 shows that all the covariates in all three models are balanced on the common support.

Having verified the balancing property, we can proceed with the computation of ATT effects for all the output variables. Table 9 shows the estimates of the ATT effects.

Let us emphasize that the computation of ATT is done on the same number of firms as there are treated firms. Namely, each treated firm is paired with one untreated firm from the control group, where the observations from the control group can be used repeatedly (i.e. we perform matching with replacement).

7.3. Robustness checking

In order to check the results of the matching model, we use instrumental-variable estimation (IV estimation). Contrary to

Table 8
Verification of balancing for all three models, common support included.

Covariates	*Subsidies only* vs. *No treatment* (n=130 on common support) Model (1)			*Tax incentives and subsidies* vs. *No treatment* (n=115 on common support) Model (2)			*Tax incentives and subsidies* vs. *Subsidies only* (n=38 on common support) Model (3)		
	Treated N=35	Control1;*N=95	p2;**	Treated N=14	Control N=101	p	Treated N=15	Control N=23	p
R&D orientation	0.29	0.29	1.00	0.29	0.29	1.00	0.40	0.40	1.00
Develop	0.06	0.06	1.00	0	0		0	0	
Lnage	2.78	2.74	0.74	2.82	2.82	0.99	2.88	2.79	0.63
Lnsize	2.57	2.34	0.48	2.73	2.42	0.42	2.75	2.71	0.94
Lnsize2	8.67	7.14	0.38	9.49	6.30	0.24	9.43	8.44	0.72
Lnexp	0.15	0.10	0.38	0.10	0.08	0.74	0.11	0.12	0.96
Lnsalestot	14.40	13.74	0.53	15.73	15.30	0.32	15.81	15.71	0.84
Nonmat	0.33	0.40	0.83	0.33	0.40	0.88	0.26	0.11	0.49
Lnprofit	0.05	0.05	0.99	0.06	0.07	0.79	0.81	0.07	0.45
*Lnage*1;**R&D*	0.85	0.80	0.89	0.84	0.81	0.95	1.18	1.17	0.98
*Lnage*1;**Lnsize*	7.59	6.82	0.48	8.14	6.94	0.47	8.33	7.76	0.74
*Lnsize*1;* *R&D*	0.99	0.87	0.76	0.91	0.74	0.76	1.25	1.32	0.92
*Nonmat*1;**R&D*	0.04	0.01	0.31	0.25	0.40	0.75	0.23	0.09	0.50
*Lnexp*1;**R&D*	0.04	0.03	0.78	0.03	0.01	0.26	0.05	0.03	0.65
High-tech	0.26	0.14	0.24	0.14	0.14	1.00	0.13	0.13	1.00
Medium high-tech	0.20	0.17	0.76	0.21	0.07	0.30	0.26	0.26	1.00
Medium low-tech	0.14	0.17	0.75	0.07	0.07	1.00	0.07	0	0.33
Low-tech	0.09	0.06	0.65	0.71	0.14	0.56	0	0.07	0.32
KIS	0.26	0.43	0.14	0.43	0.57	0.47	0.47	0.47	1.00
Techknow	0.71	0.74	0.79	0.76	0.76	1.00	0.87	0.87	1.00
p propensity score model	0.34	0.30	0.43	0.10	0.08	0.59	0.16	0.19	0.63

* N denotes the total number of observations in the control group. The means in the table are reported for matched pairs.
** p Value of t-tests on mean differences.

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Table 9
Estimation of treatment effects by Mahalanobis matching with propensity score included.

	Subsidies only vs. *No treatment* Model (1) Treated = 35, Control[a] = 95		*Tax incentives and subsidies* vs. *No treatment* Model (2) Treated = 14, Control = 101		*Tax incentives and subsidies* vs. *Subsidies only* Model (3) Treated = 15, Control = 23[d]	
	ATT	Signif. (t)	ATT	Signif. (t)	ATT	Signif. (t)
Number of employees in R&D	2.03 (0.93)	2.182;**	4.07 (1.18)	3.462;**	3.53 (1.02)	3.452;**
R&D intensity	11.71 (4.53)	2.592;**	12.29 (6.21)	1.981;*[b]	6.40 (6.33)	1.01
RI collaboration	0.34 (0.11)	3.152;**	0.57 (0.07)	5.062;**	0.20 (0.21)	0.95
Number of innovations	2.51 (1.29)	1.961;*[b]	4.28 (2.83)	1.51[c]	0.93 (2.19)	0.43
Percentage of sales from innovations	11.57 (5.77)	2.012;**	15.85 (7.95)	1.99*[b]	− 10.87 (14.34)	− 0.76
Absorptive capacity—acquisition	0.08 (0.30)	0.29	0.52 (0.38)	1.38	0.11 (0.68)	0.16
Absorptive capacity—assimilation	0.34 (0.41)	0.81	0.91 (0.56)	1.62[c]	0.22 (0.62)	0.35
Absorptive capacity—transformation	0.41 (0.32)	1.26	0.64 (0.38)	1.70[b]	0.27 (0.46)	0.58
Absorptive capacity—exploitation	0.81 (0.34)	2.352;**	1.28 (0.56)	2.28**	0.58 (0.41)	1.39

[a] Matching is performed with replacement, which means that each treated observation is matched with one control, where the control observation can be repeatedly used. Control = 95 refers to the size of the pool of control observations from which the matches are drawn.
[b] Indicates significance up to 5% in a 1-tail *t*-test.
[c] Indicates significance up to 10% in a 1-tail *t*-test.
[d] In this model treated refers to the firms that received both subsidies and tax incentives.
* Indicates significance up to 10% in a 2-tail *t*-test.
** Indicates significance up to 10% in a 2-tail *t*-test.

Table 10
Results from the first stage regression (robust standard errors used).

Dependent variable	*Subsidies only* vs. *No treatment* Model (1)	*Tax incentives and subsidies* vs. *No treatment* Model (2)	*Tax incentives and subsidies* vs. *Subsidies only* Model (3)	
	Subsidies only	*Tax incentives and subsidies*	*Tax incentives and subsidies*	
	Coeff.(S.e.)	Coeff.(S.e.)	Coeff.(S.e.)	Coeff.(S.e.)
R&D orientation	0.05(0.93)	− 0.76(0.68)	0.04(0.21)	0.04(0.22)
Develop	0.17(0.25)	− 0.05(0.19)	− 1.93(0.85)2;**	− 1.70(1.02)
Lnage	− 0.07(0.21)	− 0.25(0.17)	− 0.09(0.28)	− 0.42(0.29)
Lnsize	− 0.25(0.14)1;*	− 0.19(0.15)	0.08(0.20)	− 0.20(0.21)
Lnsize2	0.01(0.02)	0.00(0.02)	− 0.00(0.03)	0.02(0.04)
Lnexp	0.53(0.20)2;***	− 0.18(0.18)	− 0.92(0.29)3;***	− 0.90(0.28)3;***
Lnsalestot	0.00(0.02)	0.03(0.01)2;**	0.03(0.02)	0.06(0.02)3;***
Nonmat	− 0.02(0.02)	0.02(0.01)3;***	0.00(0.01)	0.00(0.01)
Lnprofit	− 0.64(0.59)	0.71(0.56)	1.28(1.76)	0.89(1.63)
*Lnage1;*R&D*	− 0.07(0.36)	0.35(0.30)	0.65(0.28)2;**	0.76(0.33)2;**
*Lnage1;*Lnsize*	0.03(0.06)	0.06(0.05)	0.01(0.07)	0.06(0.09)
*Lnsize1;*R&D*	0.20(0.10)2;**	0.00(0.12)	− 0.12(0.11)	− 0.22(0.14)
*Nonmat1;*R&D*	0.00(0.02)	− 0.02(0.02)	0.11(0.09)	0.03(0.09)
*Lnexp1;*R&D*	− 1.24(0.69)1;*	− 0.32(0.79)	1.71(0.70)2;**	1.18(0.77)
High-tech	0.04(0.17)	− 0.13(0.15)	0.08(0.28)	− 0.23(0.24)
Medium high-tech	− 0.19(0.15)	− 0.01(0.13)	0.33(0.27)	− 0.00(0.24)
Medium low-tech	− 0.15(0.15)	− 0.15(0.13)	− 0.05(0.26)	− 0.32(0.26)
Low-tech	− 0.14(0.14)	− 0.06(0.13)	0.41(0.33)	− 0.05(0.29)
KIS	− 0.30(0.14)2;**	− 0.09(0.14)	0.47(0.30)	0.07(0.26)
RAZUM	0.09(0.02)3;***			
PROGAWARE		0.15(0.04)3;***	0.12 (0.06)1;*	0.13(0.06)2;**
PATSHARE			0.41 (0.10)3;***	
BUSY				− 0.07(0.02)3;***
constant	0.76(0.45)	0.35(0.38)	− 0.60 (0.67)	0.49(0.58)
	$N = 153$	$N = 136$	$N = 60$	$N = 60$
	$F(20, 132) = 5.52$	$F(20, 115) = 4.25$	$F(21, 38) = 12.76$	$F(21, 38) = 19.80$
	Prob > $F = 0.0000$	Prob > $F = 0.0000$	Prob > $F = 0.0000$	Prob > $F = 0.0000$
	$F(1, 132) = 12.91$[a]	$F(1, 115) = 16.94$[a]	$F(2, 38) = 12.49$[a]	$F(2, 38) = 8.71$[a]

* Indicates significance up to 10%.
** Up to 5%.
*** Up to 1%.
[a] This is *F* statistics for the joint significance of the instruments excluded from the structural model.

propensity matching which assumes that factors that determine selection into treatment are all observable to the researcher, the IV approach deals with situations when the selection into treatment is driven by some unobservable factors as well. In that case, the variable describing presence of treatment becomes endogenous to the outcome variable. If Y is a dependent variable that is measured, then the IV approach requires the availability of at least one instrumental variable Z, which is (directly) correlated with the treatment, and is not correlated with the error term in the outcome Y.

It is a challenging task to find suitable instrumental variables that satisfy statistical requirements and make economic sense. For

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each model we investigated a variety of possible instruments and kept the strongest one with the best economic rational given our data set. In the model (1) we use the instrumental variable *RAZUM*, which relates to a specific subsidy program of the same name geared toward small and innovative companies. We gauged respondent awareness about a particular feature of the *RAZUM* program on a scale from 0 (not aware) to 5 (very much aware). In the model (2) we use the instrumental variable *PROGAWARE:* this is the number of different R&D&I public programs that respondents were able to name (in answer to an unaided awareness question). In both cases the rational for the choice of these instruments is the following: it is to be expected that companies applying for public aid will have higher awareness of existing public programs and their features than those that did not apply. We can argue that this awareness is a precursor to taking action and applying for a program, which would make these instruments relevant. However, this awareness should not directly influence any of the output variables except through the endogenous treatment variable which would make these instruments valid.

In the model (3) it was more challenging to find a suitable instrument, since we needed to find variables that would set apart those companies that used tax incentives together with subsidies from those that used only subsidies. For this purpose we use two instruments, one of which is *PROGAWARE*. It is to be expected that companies with better knowledge of public instruments are savvier in their use, and therefore know how to avail themselves of tax incentives as well as subsidies. As before, we argue that *PROGAWARE* does not directly influence any of the output variables. As the second instrument we choose the variable *PATSHARE,* which reports the share of the foreign patents in the patent portfolio prior to 2010. For firms that have no patents, we set *PATSHARE* to zero. The rational for the choice of *PATSHARE* is that firms which have sufficient administrative knowledge and sophistication to engage in foreign patenting are also savvier in the use of public instruments and thus take advantage of the larger portfolio of available options, which in our case means using tax incentives together with subsidies. An additional support for this choice of instrument is provided by Busom et al. (2014) finding that SMEs which utilize legal intellectual protection methods prefer tax incentives. In order to test for the validity of *PATSHARE* when used together with *PROGAWARE*, we use Wooldridge's robust score test of over-identifying restrictions which shows that it is not possible to reject the null hypothesis that these two are valid instruments for all output variables except for *Number of employees in R&D, Number of innovations, Absorptive capacity—transformation* and *Absorptive capacity—exploitation* (Table 11). For these later output variables we use the instrument *BUSY* together with *PROGAWARE*. The variable *BUSY* is 1 if the firm did not collaborate with other companies in the 2008–2010 period because it was too busy with day-to-day operations, and 0 otherwise. This variable is in negative correlation with the joint use of tax cuts and subsidies. This is as expected, because being overwhelmed with daily business activities indicates a lack of capacity or knowledge to use a larger portfolio of instruments. This can also signal that the firm may be experiencing problems and is therefore financially constrained, which contraindicates the use of tax incentives. As the first stage regression shows (Table 10), these two instruments are weaker, so the use of *PATSHARE* with *PROGAWARE* is preferred. In all cases where the instruments are used, their validity is supported by Wooldridge's robust score test of over identifying restrictions (presented in Table 11).

We used the following modeling procedure: first we checked the first-stage regression to assess the strength of the instrument. For all the instrumental variables the results of the first stage regression are presented in Table 10. For model 3 two regressions are reported because of the two different combinations of instruments.

Table 11
Verifying the need for IV estimation.

	Subsidies only vs. *No treatment* Model (1) ($n=153$)				*Tax incentives and subsidies* vs. *No treatment* Model (2) ($n=136$)				*Tax incentives and subsidies* vs. *Subsidies only* Model (3) ($n=60$)				
	Instrument	Exogeneity Ho: variables are exogenous		IV regress.	Instrument	Exogeneity Ho: variables are exogenous		IV regress	Instrument	Validity	Exogeneity Ho: variables are exogenous		IV regress
		Durbin chi2	Wu Hausman test			Durbin chi2	Wu Hausman test			Wooldridge's score chi2 test	Wooldridge's score test	Wooldridge's regression-based test	
Number of employees in R&D	*RAZUM*	0.69 ($p=0.41$)	0.60 ($p=0.44$)	No	*PROGAWARE*	2.60 ($p=0.11$)	1.96 ($p=0.16$)	No	*BUSY PROGAWARE*	0.93 ($p=0.33$)	9.22 ($p=0.00$)	11.36 ($p=0.00$)	Yes
R&D intensity	*RAZUM*	8.85 ($p=0.00$)	7.98 ($p=0.00$)	Yes	*PROGAWARE*	2.26 ($p=0.13$)	1.97 ($p=0.16$)	No	*PATSHARE PROGAWARE*	1.40 ($p=0.24$)	10.13 ($p=0.00$)	14.03 ($p=.00$)	Yes
RI collabo-ration	*RAZUM*	0.93 ($p=0.33$)	0.85 ($p=0.36$)	No	*PROGAWARE*	2.48 ($p=0.11$)	3.18 ($p=0.08$)	No	*PATSHARE PROGAWARE*	0.14 ($p=0.71$)	2.13 ($p=$ 0.14)	1.28 ($p=0.26$)	No
Number of innovations	*RAZUM*	0.02 ($p=0.88$)	0.02 ($p=0.89$)	No	*PROGAWARE*	0.53 ($p=0.47$)	0.48 ($p=0.49$)	No	*BUSY PROGAWARE*	0.88 ($p=0.35$)	3.45 ($p=0.06$)	2.71 ($p=0.11$)	No
Percentage of sales from innovations	*RAZUM*	1.28 ($p=0.26$)	1.13 ($p=0.29$)	No	*PROGAWARE*	1.66 ($p=0.20$)	1.19 ($p=0.28$)	No	*PATSHARE PROGAWARE*	1.23 ($p=0.27$)	0.40 ($p=0.53$)	0.26 ($p=0.62$)	No
Abs. cap. acquisition	*RAZUM*	8.90 ($p=0.00$)	8.25 ($p=0.00$)	Yes	*PROGAWARE*	3.73 ($p=0.05$)	5.43 ($p=0.02$)	Yes	*PATSHARE PROGAWARE*	1.77 ($p=0.18$)	4.26 ($p=0.04$)	3.28 ($p=0.08$)	Yes
Abs. cap. assimilation	*RAZUM*	0.00 ($p=0.99$)	0.00 ($p=0.99$)	No	*PROGAWARE*	2.54 ($p=0.11$)	3.20 ($p=0.08$)	No	*PATSHARE PROGAWARE*	1.54 ($p=0.21$)	0.28 ($p=0.60$)	0.17 ($p=0.68$)	No
Abs.cap. transformat.	*RAZUM*	5.54 ($p=0.02$)	5.19 ($p=0.02$)	Yes	*PROGAWARE*	3.47 ($p=0.06$)	4.60 ($p=0.03$)	Yes	*BUSY PROGAWARE*	2.51 ($p=0.11$)	4.95 ($p=$ 0.03)	3.55 ($p=0.07$)	Yes
Abs.cap. exploitation	*RAZUM*	1.12 ($p=0.29$)	0.95 ($p=0.33$)	No	*PROGAWARE*	3.18 ($p=0.07$)	3.28 ($p=0.13$)	No	*BUSY PROGAWARE*	2.23 ($p=0.14$)	9.66 ($p=$ 0.00)	8.28 ($p=0.01$)	Yes

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Table 12
Estimation of ATT using IV regression or OLS regression.

	Subsidies only vs. *No treatment* ($n=153$) Model (1)			*Tax incentives and subsidies* vs. *No treatment* ($n=136$) Model (2)			*Tax incentives and subsidies* vs. *Subsidies only* ($n=60$) Model (3)		
	ATT	Signif. *p*, $p>\lvert t\rvert$	Regression fit	ATT	Signif. *p*, $p>\lvert t\rvert$	Regression fit	ATT	Signif. *p*, $p>\lvert t\rvert$	Regression fit
Number of employees in R&D	**1.52** **(0.67)**	**0.03**	$F(20, 132)=4.96$ Prob $>F=0.00$	**2.75** **(1.05)**	**0.01**	$F(20, 115)=14.18$ Prob $>F=0.00$	**9.73** **(2.15)**	**0.00**	Wald chi2(20) = 180.95 Prob > chi2 = 0.00
R&D intensity	**32.33** **(11.61)**	**0.00**	Wald chi^2(20) = 58.61 Prob > chi2 = 0.00	**8.12** **(4.82)**	**0.09**	$F(20, 115)=3.10$ Prob $>F=0.00$	**42.46** **(15.22)**	**0.00**	Wald chi2(20) = 72.57 Prob > chi2 = 0.00
RI collaboration	**0.29** **0.09)**	**0.00**	$F((20, 132)=4.26$ Prob $>F=0.00$	**0.49** **(0.12)**	**0.00**	$F(20, 115)=5.55$ Prob $>F=0.00$	0.24 (0.18)	0.17	$F(20, 39)=5.83$ Prob $>F=0.00$
Number of innovations	2.06 (1.27)	0.11	$F(20, 132)=2.17$ Prob $>F=0.00$	1.91 (1.21)	0.12	$F(20, 115)=2.07$ Prob $>F=0.01$	1.15 (1.98)	0.57	$F(20, 39)=0.62$ Prob $>F=0.87$
Percentage of sales from innovations	**13.31** **(6.14)**	**0.03**	$F(20, 132)=2.30$ Prob $>F=0.00$	**13.82** **(6.59)**	**0.04**	Wald chi2(20) = 54.41 Prob > chi2 = 0.00	−0.92 (9.34)	0.92	$F(20, 39)=4.30$ Prob $>F=0.00$
Abs. cap. acquisition	**1.73** **(0.57)**	**0.00**	Wald chi2(20) = 42.54 Prob > chi2 = 0.00	**1.10** **0.50)**	**0.03**	Wald chi2(20) = 54.41 Prob > chi2 = 0.00	**1.15** **(0.58)**	**0.05**	Wald chi2(20) = 103.40 Prob > chi2 = 0.00
Abs. cap. assimilation	0.35 (0.30)	0.24	$F(20, 132)=1.79$ Prob $>F=0.03$	0.13 (0.34)	0.70	$F(20, 115)=2.55$ Prob $>F=0.00$	0.13 (0.42)	0.76	$F(20, 39)=1.37$ Prob $>F=0.19$
Abs.cap. transformation	**1.65** **(0.71)**	**0.02**	Wald chi2(20) = 62.65 Prob > chi2 = 0.00	**1.24** **(0.51)**	**0.01**	Wald chi2(20) = 43.46 Prob > chi2 = 0.00	**1.30** **(0.59)**	**0.03**	Wald chi2(20) = 78.50 Prob > chi2 = 0.00
Abs.cap. exploitation	**0.77** **(0.24)**	**0.002**	$F(20, 132)=5.45$ Prob $>F=0.00$	**0.72** **(0.26)**	**0.01**	$F(20, 115)=3.81$ Prob $>F=0.00$	**1.98** **(0.55)**	**0.00**	Wald chi2(20) = 78.50 Prob > chi2 = 0.00

Table 13
Treatment effects estimated by Mahalanobis matching and IV regression: confirmed, not confirmed and nonexistent.

	Subsidies only vs. *No treatment* Model (1)	*Tax incentives and subsidies* vs. *No treatment* Model (2)	*Tax incentives and subsidies* vs. *Subsidies only* Model (3)
Number of employees in R&D	**Positive, confirmed by both models**	**Positive, confirmed by both models**	**Positive, confirmed by both models**
R&D intensity	**Positive, confirmed by both models**	**Positive, confirmed by both models**	Not confirmed
RI collaboration	**Positive, confirmed by both models**	**Positive, confirmed by both models**	Non existent
Number of innovations	**Positive, confirmed by both models**	Non confirmed	Non existent
Percentage of sales from innovations	**Positive, confirmed by both models**	**Positive, confirmed by both models**	Non existent
Absorptive capacity—acquisition	Not confirmed	Not confirmed	Not confirmed
Absorptive capacity—assimilation	Non existent	Non existent	Non existent
Absorptive capacity—transformation	Not confirmed	**Positive, confirmed by both models**	Not confirmed
Absorptive capacity—exploitation	**Positive, confirmed by both models**	**Positive, confirmed by both models**	Not confirmed

In order to assess the necessity of employing an IV model vs. an OLS estimation, in model 1 and model 2 we compared a 2SLS estimation with the OLS using the Durbin chi-squared and Wu-Hausman tests for endogeneity of the treatment variable (Table 11). In model 3 we use Wooldridge's (1995) score test and a regression-based test of exogeneity. In cases where tests rejected the hypothesis of exogeneity of the treatment variable, we used IV 2SLS estimation as suggested in Wooldridge (2002).

The effects obtained by the IV or the OLS estimation are provided in Table 12. The results mostly confirm the matching outcomes, but there are some discrepancies. More precisely, in model (1) the effect on the variable *Number of innovations* was not confirmed, and in model (2) the effect on *Absorptive capacity—transformation* was not confirmed.

Table 12 shows that IV or OLS regressions yield significant effects on some dimensions of absorption capacity which were not confirmed by matching. From now on we will take into account only those effects that were confirmed by both models. Table 13 presents the effects that were confirmed by both the Mahalanobis matching with the propensity score, and by IV or OLS regression.

7.4. Results: summary of both matching and IV regression

Table 13 summarizes our quantitative results in the following way: by "positive, confirmed" we denote situations in which both Mahalanobis matching and IV regression yield a positive significant result. By "not confirmed" we denote situations in which they differ, and by "nonexistent" we denote cells where no effect was found by either method.

Table 13 shows that compared with no treatment, subsidies used alone or with tax incentives improve all of the examined aspects of R&D, thus confirming Hypotheses 1A and 1B. Regarding innovation output, subsidies used alone or jointly with tax incentives increase the percentage of sales from innovations, partially supporting Hypothesis 2. The positive effect that the use of both instruments has on the number of innovations was not supported by IV estimation for the model (2). Hypothesis 3 is also partially supported, because subsidies used alone or with tax incentives have a positive effect on the exploitation aspect of absorptive capacity, while the joint use of the instruments also has a positive impact of the acquisition aspect. Although Table 9 shows that the use of both instruments improves other aspects of absorptive capacity compared to the control group, this was not confirmed by IV estimation.

Although Table 13 suggests that the joint use of the aforementioned instruments is more effective when compared to the control group (model (2)), when we compare the firms that used both instruments with those that used only subsidies (model (3)), this effect disappears. The only exception is the variable *Number of R&D employees*, which shows an advantage in the firms using tax incentives together with subsidies over those using subsidies only. This means that Hypothesis 4 is supported in only one of the nine investigated effects.

8. Discussion

Compared to firms that did not use public instruments, direct grants alone or used jointly with tax incentives improve R&D input and affect R&D behavior. Our data shows that SMEs which received direct grants have a significantly higher R&D intensity, which confirms findings from Herrera and Sánchez-González (2013) for Spain, and Reinkowski et al. (2010) for East Germany. Direct grants increase R&D employment in SMEs, thus supporting findings from Czarnitzki and Lopes-Bento (2013) for Flanders. Both findings are also true for SMEs which used tax incentives in addition to direct grants. These results indicate a strengthening of the R&D orientation in recipient firms.

Direct grants with or without tax incentives positively affect the percentage of sales from innovation. The increase in this quantity indicates stronger orientation toward innovation and faster moving innovation portfolio. This confirms the results from Hottenrott and Lopes-Bento (2014) for Flanders. While the percentage of sales from innovation increases, there is no definite effect on the number of innovations. This may indicate that public instruments allow companies to achieve improvements in the quality rather than the quantity of innovations.

Public instruments induce changes in firm behavior. Our data shows that SMEs which received subsidies (with or without tax incentives) are more likely to collaborate with research institutions than firms that did not take advantage of the public instruments available to them. This collaboration brings about transformation by introducing new capabilities and knowledge. In general, the value of knowledge increases and the treatment of knowledge changes, as is evident from looking at the alterations in absorptive capacity.

Public instruments do induce changes in absorptive capacity, but not equally in its every aspect. Exploitation is clearly the dimension which is affected both by the use of subsidies alone and by their joint use in combination with tax incentives (compared to the use of no instrument). It is also the only dimension of absorptive capacity that is affected by the use of subsidies alone. This may be driven by the fact that grants are given for specific projects, which gives them a comparatively "narrow" focus that centers on the exploitation of existing knowledge in order to commercialize innovations. The generation of abilities in order to acquire, assimilate and transform new knowledge is not as crucial in justifying a grant whose purpose is delivering specific proposed results. In contrast, the use of both instruments compared to the use of no treatment also seems to increase transformation dimension. It is possible that this effect could be attributed to tax relief incentivizing firms in a way different from direct grants. A tax instrument is less focused than a subsidy, and so the firm can conduct its innovation process in a less controlled way. This lack of restrictions encourages a larger scope of activities, which allows for the development of other dimensions of absorptive capacity. In this way, tax incentives and subsidies act as complements in building different capabilities.

Although we can find definite discrepancies when recipient SMEs are compared to those that did not use public schemes, we do not find many decisive differences when we compare the grant recipients which used tax incentives with those that used only grants. The only effect which is confirmed by both matching and IV regression is an increase in the number of R&D employees, which suggests that the use of tax incentives allows companies to increase their R&D capacity. As for other effects, while IV regression detects the differences in absorptive capacity and R&D intensity and thus suggests that the use of both instruments achieves better results for these dimensions, the matching method does not confirm these findings. Neither of the two methods discovered any effect on innovation output, which may suggest that tax incentives are used for small projects that do not necessarily end up in a new product.

Although none of these effects are confirmed, with the exception of the increase in the number of R&D employees, their direction is as expected (i.e. using both instruments produces stronger effects). This absence of confirmed effects suggests that tax incentives may have limited usefulness for SMEs. In fact, our data indicates that direct grants may be dominant to such a degree that the addition of tax incentives does not bring significant benefit if compared to subsidies alone. The explanation can be linked back to the fit between the instrument and characteristics of SMEs. As discussed previously, in contrast to direct grants where funds are awarded before the work starts, a firm can claim tax relief only for R&D that has already been performed using private funding. Since SMEs cannot invest heavily in R&D due to restricted resources, the amount of R&D that can be performed due to tax incentives is likely to be inadequate for more ambitious projects. This in turn will limit the effectiveness of tax incentives in increasing a firm's R&D input, innovation output or absorptive capacity. Potential appropriability problems are also likely to limit the usefulness of tax incentives, as firms with this difficulty are likely to seek subsidies as their primary choice of instrument. To sum up, we can expect SMEs to fund their large and ambitious projects using direct grants, and to use tax incentives to support smaller and less demanding middle-of-the-road projects. Since the large projects funded by subsidies will fuel a firm's R&D&I growth while the small projects will account for small advances, we can expect that the most benefit to R&D&I will come from subsidies, while the effect of adding tax incentives will be weak. Having stated that, we recognize that the degree to which these additional effects appear may depend on the data source (i.e. the country or the industry). For example, in a country (or an industry) where SMEs are more financially constrained, the actual benefit obtained from tax incentives would likely be smaller, while these effects are expected to increase in countries or industries where SMEs have easy access to affordable private funding for R&D investment.

9. Conclusion

Although large and small firms innovate in different ways, so far limited empirical evidence has been reported with respect to the effectiveness of R&D instruments for SMEs (Reinkowski et al., 2010; Herrera et al., 2010). Our data suggests that direct subsidies used alone or jointly with tax incentives strengthen the R&D orientation of the firm as well as the innovation output. Our study implies that public instruments reach beyond input and output to affect the recipient firm on a deeper and more enduring level by affecting aspects of absorptive capacity, a crucial firm capability. As any transformations of absorptive capacity become deeply ingrained in the firm, the changes brought about by public instruments will have a profound effect on future ability to innovate and create competitive advantage. By making it possible for SMEs to increase absorptive capacity, there is hope that public instruments can enable a recipient firm to permanently elevate itself onto a higher level of innovation ability. Thus an effective public instrument may go beyond reducing the cost of R&D to become an agent of organizational transformation.

Although we can see definite effects of policy measures when comparison is made against firms that did not use any of the two instruments, it seems that adding tax incentives to a direct grant does not bring much additional improvement. This lack of pronounced difference is not a reflection on the merits of tax relief as an instrument; instead this result illustrates limitations related to the use of tax incentives in SMEs. As tax relief can be claimed only after the funds are expended, inadequate financial resources may

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limit the usefulness of tax relief, resulting in the lack of expected effect. This situation can be exacerbated if the SME operates in a country where access to outside capital for R&D is limited (lack of venture capitalists, business angels, investment funds, reasonable bank loans, etc.). Another possible problem that cannot be resolved by the use of tax incentives is the threat of competitive imitation. In this sense we confirm Busom et al. (2014) in finding that tax incentives may not be the best instrument to alleviate the causes of market failure in SMEs, while direct subsidies are more suitable. The complementary use of tax incentives and subsidies on the policy level found by Busom et al. (2014) has its counterpart in complementary use on the level of the firm's project portfolio. Namely, the two instruments are appropriate for different types of R&D projects: large, innovative projects with possibly smaller private returns are better suited for subsidies, while limited and more routine projects can be better supported by tax incentives. Having said that, we recognize that the extent to which the grant users will benefit from the additional tax incentives may depend on the characteristics of the country or the industry. For example, in a country (or an industry) where SMEs have good access to affordable private funding for R&D investment the actual benefit obtained from tax incentives will likely be higher. For the same reasons we can expect that in developing countries subsidies will be a more efficient instrument for fostering R&D in SMEs. The size of the effect and the determination of mediating factors is a question which merits further research.

This study has a number of limitations. While it is true that the matching estimator is frequently used in literature to estimate the effect of policies on certain outcome variables, it is also linked to a number of drawbacks. It only controls for observables, which means that the conditional independence assumption has to hold for the results to be valid. Finding a larger number of potential covariates lessens this problem. As in our case we are constrained by the nature of the available data, we try to address this by checking the robustness of our results by modeling unobservables via IV estimation. Our study could better address the effectiveness of public instruments if we had access to full information about the funded projects. In other words, we only have firm-level data while the funding agency has information on the details of the R&D project it evaluates in the funding decision (such as information on the amount of the subsidies). We plan to address these limitations in future research. Repeating the study on a larger dataset would insure that the lack of some expected effects is not caused by small sample size.

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Appendix A

The conditional independence assumption (CIA) states that potential treatment outcomes are independent of the assigment mechanism for any given value of a vector of attributes X in a particular attribute space χ. Formally, denote by S the variable that indicates participation in either of the treatments, $S \in \{0,1\} \times \{0,1\}$. Then the CIA assumption is stated as

$$Y^{0,0}, Y^{0,1}, Y^{1,0}, Y^{1,1} \coprod S | X = x, \forall x \in \chi, \tag{1}$$

Since the four pairs of possible outcomes are mutually exclusive, following the arguments of Lechner (1999) we can prove that the conditional independence assumption (CIA) implies the generalized balancing score property analogously.

Proposition. Denote by S the variable that indicates participation in either of the treatments, $S \in \{0,1\} \times \{0,1\}$:
If

$$E\left[P(S=m|X=x)|b(X)=b(x)\right] = P[S=m|X=x] = P^m(x), \tag{2}$$

when $0 < P^m(x) < 1$, $\forall m \in \{0,1\} \times \{0,1\}$, and $Y^{0,0}, Y^{0,1}, Y^{1,0}, Y^{1,1} \coprod S|X=x, \forall x \in \chi$, then $Y^{0,0}, Y^{0,1}, Y^{1,0}, Y^{1,1} \coprod S|b(X)=b(x), \forall x \in \chi$ for all suitable functions b of X, in particular the balancing score.

Proof. Let $F(S|Z)$ denote the distribution function of S conditional on some vector of variables Z. We need to show that

$$F(S|Y^{0,0}, Y^{0,1}, Y^{1,0}, Y^{1,1}, b(X)) = F(S|b(X)) = F(S|X). \tag{A.1}$$

since S has four possible values, $F(S|X)$ is a discrete function with four values for every given value x of χ. Therefore, (A.1) can be rewritten as

$$\begin{aligned} &P(S=m|Y^{0,0}, Y^{0,1}, Y^{1,0}, Y^{1,1}, b(X)) \\ &\quad = P(S=m|b(X)) = P(S=m|X), \forall m \in \{0,1\} \times \{0,1\} \end{aligned} \tag{A.2}$$

First we note that the second equality in (A.2) holds directly from assumption (2). To show the first equality, we can calculate:

$$\begin{aligned} &P(S=m|Y^{0,0}, Y^{0,1}, Y^{1,0}, Y^{1,1}, b(X)) \\ &\quad = E[P(S=m|Y^{0,0}, Y^{0,1}, Y^{1,0}, Y^{1,1}, X)|Y^{0,0}, Y^{0,1}, Y^{1,0}, Y^{1,1}, b(X)] \end{aligned}$$

This holds by the basic property of conditional expectation:
$E\left[E\left[X|\delta_2\right]|\delta_1\right] = E\left[X|\delta_1\right]$ when $\delta_1 \le \delta_2$, for any sigma-algebras δ_1, δ_2.(∗)

The CIA states that $P(S=m|Y^{0,0}, Y^{0,1}, Y^{1,0}, Y^{1,1}, X) = P(S=m|X)$, therefore: $\begin{aligned} &P(S=m|Y^{0,0}, Y^{0,1}, Y^{1,0}, Y^{1,1}, b(X)) \\ &= E[P(S=m|X)|Y^{0,0}, Y^{0,1}, Y^{1,0}, Y^{1,1}, b(X)] \end{aligned}$.

From assumption (2) it follows that $E\left[P(S=m|X=x)|b(X)=b(x)\right]$ does not depend on the potential outcomes, therefore the previous expression is equal to $E\left[P(S=m|X)|b(X)\right]$.

Again from property (∗) we have that $E\left[P(S=m|X)|b(X)\right] = P(S=m|b(X))$, so from all previous calculation it follows that (A.2) holds and we have the desired balancing score property.

Q.E.D.

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