

Additionality effects of public support programmes on cooperation for innovation: evidence from European manufacturing SMEs

Abstract

We have witnessed an increase in the number of research studies focusing on the behavioural additionality effects of research, development and innovation (RD&I) policy – where this form of additionality measures the impact of public support measures on firms' behaviour thought to promote innovation. This paper considers whether public support increases the propensity of small and medium-sized enterprises (SMEs) in traditional manufacturing industries to cooperate for innovation. Drawing on a unique dataset of SMEs from six manufacturing industries across seven European Union (EU) regions, we estimated treatment effects by applying a range of matching estimators. The results suggest a positive yet heterogeneous impact of public support on cooperation for innovation in the sample SMEs. Overall, the largest treatment parameters refer to public-private partnerships. Following best practice in matching estimation, the study reports its findings from a novel simulation-based sensitivity analysis, which indicates that the estimated treatment parameters are robust with respect to any possible unobserved heterogeneity.

Keywords: Behavioural additionality; Cooperation for innovation; Innovation policy; SMEs; Traditional manufacturing industry; Policy Evaluation

1 Introduction¹

Evaluation of innovation policies, until recently, was mainly concerned with input and output additionalities. Focusing on innovation inputs and outputs, however, means that we stay outside the “black box” of innovation processes by observing either the beginning (innovation inputs) or end results (innovation outputs) of those processes (OECD, 2006). Behavioural additionality enables us to go beyond input and output additionalities and assess the impact of public measures on firms' innovative behaviour (Buisseret et al., 1995; Georghiou and Clarysse, 2006). The literature lacks a common definition for behavioural additionality, with a broad perspective being advanced. However, most empirical studies investigate only one category (Georghiou and Clarysse, 2006); that is the impact of public intervention on firms' cooperative behaviour (scope additionality as defined by Falk, 2007; or network additionality if adopting the OECD, 2006, definition). In other words, scope or network additionality occurs when the likelihood of cooperating for innovation increases as a result of participation in support programmes (Busom and Fernández-Ribas, 2008). And whilst not the focus of this paper, one further category of behavioural additionality has been termed cognitive capacity additionality, where a positive impact of public measures on managerial competencies and expertise is observed (Bach and Matt, 2005; Falk, 2007).

We draw on a unique dataset of SMEs mainly in six manufacturing industries across seven EU regions, and employ several matching estimators to investigate the impact of public support measures on cooperation for innovation. Because all of the SMEs in the dataset are in manufacturing industries commonly described as “traditional”, and few such firms receive support for conventional R&D, the support measures investigated in this paper are ones designed to promote innovation outputs more “broadly” (as defined in the *Oslo Manual*: OECD, 2005).² A previous study evaluated the effect of these support measures in promoting output additionality among the SMEs surveyed, which are overwhelmingly innovative in the

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²Wintjes et al. (2014, p. 6), one of few studies on innovation policy support for SMEs in traditional industries, provide support for this focus: “Data from the Innobarometer 2003 show that fewer firms in traditional industries (6 per cent) receive direct support to finance R&D based innovation projects than firms in other manufacturing industries (10 per cent) or services (8 per cent).”

http://ec.europa.eu/enterprise/policies/innovation/policy/innobarometer/index_en.htm

broad sense whether or not they participated in support programmes (Radicic et al., 2014).³In contrast, this study focuses on the effect of these support measures from the perspective of behavioural additionality.

In general, public intervention can result in additionality (or complementarity) of public funding and firms' private innovation activities, or it might produce a crowding-out effect, whereby public funding substitutes firms' own privately funded activities (Busom and Fernández-Ribas, 2008; Cerulli, 2010). As with other empirical studies on behavioural additionality, the available dataset does not allow for the exploration of all forms of behavioural additionality, subsequently we focus on evaluating cooperation (network or scope) additionality.

Due to often noted factors hampering econometric analysis, such as lack of longitudinal data and valid instruments for selection models (Busom and Fernández-Ribas, 2008; Czarnitzki et al., 2007), matching estimation has become a widely used evaluation method in the literature on the effectiveness of innovation policy. Our main research question is whether or not public support measures are effective in fostering cooperative behaviour among manufacturing SMEs? As matching estimators can only control for observed heterogeneity, we apply sensitivity analysis as an integral part of the study (Guo and Fraser, 2010). However, to the best of our knowledge, only one similar study, Alecke et al. (2012), follows this best practice by reporting the results of sensitivity analysis. Therefore, given that the objective of sensitivity analysis is to indirectly test whether estimated treatment effects are biased due to unobserved factors, we report the findings of our simulation-based sensitivity analysis (Nannicini, 2007).

This study departs from existing empirical literature by focusing on the behavioural additionality in SMEs as well as by conducting sensitivity analysis to indirectly test one of the main assumptions underlying matching estimators. In addition, we test the hypothesis advanced by Georghiou (2002) on the substitutability of output and behavioural additionality (Clarysse et al., 2009). Namely, Georghiou (2002) noted that behavioural additionality might take place even when public support measures do not induce input and output additionality. A previous study by Radicic et al. (2014) analysed the same dataset as the one employed in this study and, overall, found no evidence of output additionality. Hence, this study was partly motivated by Georghiou's hypothesis on the occurrence of behavioural additionality as a

³ Respectively, 99 per cent of the SMEs receiving publicly-funded innovation support and 90 per cent of those not receiving such support in the sample period undertook one or more activities consistent with the “broad innovation” concept – i.e. including product, process, organisational and marketing innovation (OECD, 2005).

substitute for the lack of output additionality – where we focus on the propensity to cooperate in innovation activity as a consequence of public support measures.

The paper is organised as follows: Section 2 reviews the rationales for public intervention in innovation and reviews empirical evidence. Section 3 formulates the methodological framework, while Section 4 discusses model specifications and the data used in the study. Section 5 gives the main results from matching estimators and discusses findings from the added sensitivity analysis. In Section 6 we draw our conclusions.

2 Behavioural additionality - rationale and empirical evidence

Within the domain of additionality effects, input and output additionalities arise from the traditional (or neo-classical) notion of market failure, while a broader concept of behavioural additionality has emerged from the evolutionary, system failure rationale (Antonioli and Marzucchi, 2012; Clarysse et al., 2009; Georghiou and Clarysse, 2006; Gök and Edler, 2012). Traditional (or neo-classical) market failure refers to inefficient allocation of goods and services in a market due to externalities, asymmetric information, non-competitive markets, uncertainty and risk, appropriability issues, indivisibility of knowledge generation, imperfect capital markets and missing markets for high-risk investments (Arrow, 1962; Nelson, 1959). From the late 1950s onwards, this market failure rationale has provided a basis for public innovation policies (Hobday, 2005; Schröter, 2009).

The evolutionary approach of systemic failures has been developed since the 1990s as a corollary to the development of evolutionary economics and of a resource-based, evolutionary theory of the firm (Bleda and del Río, 2013; Smits, 2002; Woolthuis et al., 2005). Systemic failure and market failure approaches are not mutually exclusive, but can be complementary to each other (Clarysse et al., 2009; Georghiou and Clarysse, 2006; Smits, 2002). As the linear model of innovation was heavily criticized, with the development of evolutionary economics and of later generations of innovation models (from the Kline-Rosenberg chain-linked model to the fifth generation of networking models) (Rothwell, 1992), the innovation process is regarded as a non-linear process (Lundvall, 1988), involving not just innovative firms but entire innovation systems, including all economic actors and institutions and organizations affecting firms' innovativeness (Mytelka and Smith, 2002; Woolthuis et al., 2005).

The emergence of evolutionary theorizing on innovation, and corresponding system perspectives, has resulted in a shift in the design of innovation policy and its ensuing

evaluation, by focusing on behavioural additionality (Antonioli and Marzucchi, 2012; Gök and Edler, 2012). Georghiou (2002) hypothesized that behavioural additionality can occur as a consequence of public interventions when input and output additionality do not take place (Clarysse et al., 2009). A previous study by Radicic et al. (2014), using the same dataset as the present study, found that no output additionality was observed among the SMEs surveyed. Thus, in this study, our additional objective is to test the hypothesis by Georghiou (2002) that behavioural additionality might be a substitute for the lack of output additionalities (Clarysse et al., 2009). In this context, the current study is a continuation of the investigation of additionality effects of innovation policy on innovation activities in SMEs.

Compared to a sizeable number of empirical studies on input additionality and, to a lesser extent, on output additionality, behavioural additionality has been the subject of only a few studies (Antonioli and Marzucchi, 2012; Busom and Fernández-Ribas, 2008; Cunningham and Gök, 2012). Although scarce, empirical studies on behavioural additionality mostly report a positive innovation policy effect (Busom and Fernández-Ribas, 2008; Fernández - Ribas and Shapira, 2009; Fier et al., 2006; Hyvärinen, 2006). In addition, most of these studies report larger additionality effects for public-private partnerships than for cooperation with other businesses (Busom and Fernández-Ribas, 2008; Fier et al., 2006). By contrast, Afcha- Chàvez (2011) and Antonioli et al. (2014) report no innovation policy effects on vertical cooperation (with customers and suppliers), while the latter even found a negative impact of regional policy on horizontal cooperation (with competitors). In summary, most studies report behavioural additionality, but the magnitude and significance vary depending on types of cooperative partnerships. Therefore, based on the extant literature, we posit the following hypothesis:

Hypothesis: Innovation policy effects are positive, but will vary depending on the type of cooperative partnership supported. In particular, it is expected that larger effects are found for public-private associations, rather than for other types of cooperative relationships.

Section 2.1 discusses the literature that informs our expectation of this particular effect.

2.1 Cooperation for innovation

The advantages of cooperation for innovation are arguably many. The main argument is that cooperation for innovation reduces costs, because firms can exploit economies of scale and scope (Hagedoorn, 1993; Teirlinck and Spithoven, 2012). Second, through cooperation firms

share risk and uncertainty related to innovation processes (Hagedoorn, 1993; Rese and Baier, 2011). Third, transaction costs theory suggests that firms will opt to 'buy', instead of 'make', when transaction costs are low. Similarly, when transaction costs are high, in order to economize on these costs, firms are more likely to conduct innovation activities internally. In contrast, cooperation, treated as a hybrid form of corporate governance in the transaction costs framework, is pursued when technological dealings entail low transaction costs (Williamson, 1985).

Inter-firm cooperation for innovation offer time advantage compared to internal technology and innovation development, which means that firms can commercialize their inventions in a shorter time interval (Rese and Baier, 2011). This is particularly relevant for small firms, insofar as patenting and other formal mechanisms for appropriating intellectual assets are less often utilized by SMEs. The reasons are usually related to high costs of patent application and difficulties in maintaining secrecy in joint innovation projects. Leiponen and Byma (2009) found that the most important method of protecting IPs in Finnish SMEs is speed to market. Therefore, in order to capture innovation returns and overcome appropriability issues, the most effective mechanism is quick market launch of new or improved technologies and innovations.

Hoffmann and Schlosser (2001) investigate determinants of successful cooperation in Austrian SMEs. Their findings reveal that SMEs greatly underestimate some of the critical success factors, such as partnership governance and professional management. SMEs should continuously dedicate their resources and management competencies to a successful appropriation of benefits from cooperation. However, SMEs often lack the managerial skills and experience necessary for developing and maintaining successful cooperative ties.

Mutual trust between partners is often identified as a key success factor in collaborative relationships (Barge-Gil, 2010; Lee et al., 2010). As a potential licensee can behave opportunistically and obtain information about new technologies without paying for them, firms may lack incentives to reveal their internal inventions. To avoid this “disclosure paradox”, inventors often require a formal agreement with a licensee (Dahlander and Gann, 2010). Love and Roper (2005) confirms this argument, suggesting that firms deciding whether to internalize or outsource technological competencies are primarily concerned with protecting information leakages rather than with exploring economies of scale and scope. Furthermore, empirical studies regularly report that weak appropriability has a negative effect on cooperation for innovation (Lhuillery and Pfister, 2009). Barge-Gil (2010) conclude that forcing firms to collaborate can be counterproductive and creates a climate of mistrust.

Finally, Lee et al. (2010) discuss potential negative effects of cooperation in the context of small and medium-sized firms: namely, an increased likelihood of leakage of core knowledge, which can jeopardize firms' competitive advantage; and higher levels of mistrust that require monitoring of partner's behaviour, which, in turn, increases costs.

Following Busom and Fernández-Ribas (2008), public support measures might help firms to overcome barriers to cooperation as well as to mitigate cooperation failure. Cooperation failure refers to reduced effort in cooperative partnerships when cooperating firms do not clearly specify which partner will be assigned exclusive property rights (Dhont-Peltrault and Pfister, 2011). Regarding a particular type of cooperative partner, SMEs might face a higher risk of cooperation failure in cooperating with competitors (Lhuillery and Pfister, 2009). The reason for an increased risk is that competing firms could try to capture the other firm's knowledge, while at the same time, trying to minimize the transfer of their own knowledge to the other firm. A low proportion of firms cooperating with competitors can be taken as an indicator of difficulties in managing this type of cooperation. Of interest, the surveyed firms in our sample confirm this hypothesis, as the smallest number of firms (only 8 per cent) cooperate with competitors, while the largest number engage in vertical cooperation with customers and suppliers (see Section 4.1), which is found to be not unusual with respect to cooperation for innovation (Lhuillery and Pfister, 2009). Finally, given the prominent role of trust in cooperative innovation, firms are less likely to trust their competitors than, for instance, government institutions which, contrary to competing firms, are willing to share knowledge with enterprise, while posing no commercial threat. Thus, appropriability issues and mistrust are least likely to take place in public-private partnerships. In sum, following Lhuillery and Pfister (2009), the risk of cooperation failure is of high importance when a firm decides whether to cooperate for innovation with a particular partner.

3 Methodology

Measuring the impact of a treatment includes economic agents (firms, households, and individuals), potential outcomes and the actual treatment. If we denote T_i to be participation in public support ($T_i = 1$ if the firm i received public support and $T_i = 0$ if not) and Y_i to denote the outcomes of firms $i = 1, \dots, N$, where N is the total population of firms, Y_{i1} is the outcome of subsidized firms, Y_{i0} is the outcome of subsidized firms had they not receive public support, and Δ_i is the treatment (additionality) effect for the firm i , then:

$$\Delta_i = Y_{i1} - Y_{i0} \quad (1)$$

Eq. (1) points to the fundamental evaluation problem. To evaluate the impact of a treatment, both outcomes with and without treatment should be simultaneously observed. Therefore, the outcome for treated firms had they not been treated (counterfactual outcome - Y_{i0}) cannot be observed and has to be estimated, which implies that the treatment effect itself cannot be observed and must be estimated (Heckman et al., 1997).

We are interested in estimating the Average Treatment Effect on the Treated (ATT), which indicates the difference in outcomes of the treated firms with and without treatment and can be written as:

$$ATT = E[Y_1|T = 1] - E[Y_0|T = 1] \quad (2)$$

The first term on the right-hand side of Eq. (2), $E[Y_1|T = 1]$, is the expected outcome for treated firms conditional on their participation, while the second term $E[Y_0|T = 1]$ is the expected outcome had treated firms not participated in the public support programme. This second term refers to a counterfactual outcome that is not observed. If the unconditional outcome of non-subsidized firms is taken to estimate the counterfactual outcome, then that would lead to selection bias, as treated and non-treated firms may differ even before a treatment assignment (Heckman et al., 1997). Evaluation methods are designed to estimate counterfactual outcomes while controlling for selection bias.

Evaluation methods in cross sectional settings include structural and non-structural models (Cerulli, 2010). The former refers to selection models and Instrumental Variables (IV) approaches, whereas the latter includes matching estimators, such as Propensity Score Matching (PSM), which is the most frequently used estimator in innovation studies (Cerulli, 2010; Herrera and Nieto, 2008). According to Cerulli (2010), structural models are more theoretical than non-structural reduced form models. The latter models are a-theoretical and more data driven and these models dominate the evaluation literature on the additional effects of R&D and innovation policy.

The main advantage of matching estimators, compared to selection models and IV approaches, is that they do not require any distributional assumptions regarding the error terms in the selection equation and in the outcome equation. Conversely, the main limitation of matching estimators is selection on observables, i.e. the method only controls for firms' observed characteristics (Caliendo and Kopeinig, 2008; Guo and Fraser, 2010; Nannicini, 2007). In cases when unobserved inferences are suspected to influence the treatment assignment, matching yields biased estimates of treatment effects. Matching as an evaluation

method is based on two assumptions. The first identifying assumption is referred to as the conditional independence assumption (CIA), unconfoundedness or selection on observables (Imbens, 2004; Imbens and Wooldridge, 2009). This condition states that both counterfactual outcomes, Y_0 and Y_1 , are independent of a treatment assignment T , conditional on observed covariates X . The CIA is a strong assumption and requires that all relevant observed variables are included in the estimation of treatment effects and that variables are measured before treatment assignment (or that they measure fixed effects or slow-moving firm characteristics). The second identifying assumption refers to the overlap or common support condition, which states that both treated and non-treated firms have a positive probability of receiving a treatment or not (thus avoiding perfect predictability of a treatment assignment conditional on X).

Regarding choice among the PSM methods, Nearest Neighbour (NN) matching is the most commonly used estimator in the innovation literature (Czarnitzki et al., 2007; Herrera and Nieto, 2008). In applying the Nearest Neighbours (NN) estimator, subsidized (treated) firms are matched with non-subsidized firms (as a control group) based on the estimated propensity scores. The crucial step in the matching procedure is the choice of covariates X . The literature suggests that all observed variables that simultaneously affect a treatment and outcome should be included in the estimation of propensity scores (the selection equation) (Austin, 2011; Caliendo and Kopeinig, 2008; Steiner et al., 2010). Following Steiner et al. (2010), in situations when researchers have little or no information on the selection mechanism (which is usually the case in innovation studies), the optimal modelling strategy is to include a large set of covariates, because this approach increases the probability of satisfying the assumption of selection on observables, i.e. strong ignorability.

The next step in the PSM is the estimation of the propensity score. Since the propensity score is a probability of receiving a treatment (in our case, public subsidies), researchers can choose any discrete choice model, because both probit and logit models usually yield similar results (Caliendo and Kopeinig, 2008). After the estimation of the propensity score, but prior to applying a chosen matching estimator, a balancing test should be conducted. The purpose of a balancing test before matching (stratification test) is to check how well the estimated propensity score has succeeded in balancing covariates. We applied the procedure by Becker and Ichino (2002), similar to the study by Herrera and Nieto (2008). After the propensity score is estimated and matching quality is satisfactory, the matched pairs of treated and non-treated firms are created, based on the estimated propensity score. Finally,

the Average Treatment Effect on Treated (ATT) is calculated by taking the mean difference in the outcome variables of treated and non-treated firms.

As a robustness check, the literature on evaluation methods recommends the estimation of treatment parameters applying different matching estimators (Guo and Fraser, 2010). Although in large samples there should be no variations in treatment parameters computed by different estimators, this assumption might not hold in small samples (Herrera and Nieto, 2008). Following best practice in the literature on matching estimators, we apply two matching estimators for a robustness check. The first is kernel matching, which uses weighted averages of most units in the control group to estimate a counterfactual outcome (Guo and Fraser, 2010).⁴ The major advantage of this non-parametric estimator is the reduction in variance as the entire sample of the control group is used in the matching algorithm. Kernel matching requires the selection of the kernel function (e.g. Gaussian, Epanechnikov) and of the bandwidth parameter, although the former is not very relevant in practice. The choice of bandwidth is associated with the following bias; high bandwidth yields a diminishing variance at the price of biased estimates and vice versa (Caliendo and Kopeinig, 2008; Guo and Fraser, 2010).

The second PSM estimator used for robustness check is Inverse Probability of Treatment Weighting (IPTW) based on a propensity score (derived by Wooldridge, 2007), which uses weights based on the propensity score to create an artificial population in which treatment assignment is independent of the exogenous covariates X . The purpose of weighting is similar to using survey sampling weights to obtain weighted survey samples that are representative of the population (Austin, 2011). After estimating the weights, the next step is to estimate the regression function by weighted least squares, whereby the outcome variable is regressed on the treatment indicator and covariates X . The weights, in this case, ensure that the treatment indicator is not correlated with the covariates. The variance estimation of the IPTW estimator has to take into account that weights are used to create an artificial sample. It is a common practice to use robust variance estimation (Austin, 2011; Emsley et al., 2008; Nichols, 2008). This estimator belongs to a group of double robust estimators, which require modelling both the propensity score model and a regression model by the same estimator. The importance of this estimator lies in its double robustness property, i.e. it remains consistent if either the propensity score model (the selection equation) is correctly specified or the regression model (the outcome equation), or both. Therefore, only

⁴How many comparison units will be used depends on the choice of bandwidth.

one model needs to be correctly specified for consistent estimation (Imbens, 2004; Imbens and Wooldridge, 2009; Wooldridge, 2007).

4 Data and variables

4.1 Data

This study employs a unique survey dataset gathered in 2010, while the survey questionnaire covers the period 2005-2009. The sample of 312 SMEs - fewer than 250 employees - is dominated by innovating firms, as almost all firms (94 per cent) had engaged in innovative activities by introducing some type of technological (product and process) and/or non-technological (organizational and marketing) innovations (for definitions, see the *Oslo Manual*, OECD, 2005). Moreover, the sample includes SMEs from seven EU regions and mainly (80%) belonging to one of six manufacturing industries strongly represented in these regions: West Midlands (United Kingdom), North Brabant (Netherlands), Saxony-Anhalt (Germany), Limousin (France), Norte-Centro (Porto/Aveiro, Portugal), Comunidad Valenciana (Spain) and Emilia-Romagna (Italy); and leather and leather products; ceramics or other non-metallic mineral products; textiles and textile products; mechanical/metallurgy or basic metals and fabricated metal products; automotive or motor vehicles, trailers and semi-trailers; and food products and beverages.⁵

Descriptive statistics are presented in Appendix Table A1. Fewer than half of the surveyed firms (45 per cent) participated in one or more public support programmes in the period covered by the survey. The modal firm in the sample had 35 employees.⁶ Slightly more than one fifth (23 per cent) of firms had experienced strong competitive pressure. On average, the surveyed SMEs exported 20 per cent of their sales. Slightly more than a third (37 per cent) of firms invested more resources in innovation in 2009 than in 2005. With respect to firms' innovation capabilities in 2005, the largest number of firms (27 per cent) self-reported above average or leading capabilities in product innovation, whereas the smallest number (13 per cent) reported above average or leading capabilities in organizational innovation. Regarding cooperation partners, the largest number of firms stated that they engaged in

⁵For detailed information about sampling and the survey, see <http://www.gprix.eu/>.

⁶The proportion of micro, small and medium-sized firms in the sample is reasonably well balanced: 33 per cent are micro firms with fewer than 10 employees; 43 per cent are small firms with 10 or more and fewer than 50 employees; and 24 per cent are medium-sized firms with 50 or more and fewer than 250 employees (see Appendix Table A1).

vertical cooperation (34 per cent of firms cooperated with customers and 33 per cent with suppliers), followed by cooperation with Universities and HEIs (31 per cent) and with consultants (23 per cent). A small number of firms stated they engaged in horizontal cooperation with their competitors (8 per cent).

4.2 Model specification

The treatment variable (*Participation*) is a binary indicator equal to 1 if the firm responded positively to the question: "Did your enterprise during the five years 2005 to 2009 receive any public support for your innovation activities?" The eight outcome variables measuring firms' cooperation activities are defined as binary indicators equal to 1 if the firm cooperates with the following potential partners (and zero otherwise): suppliers (*Coop_suppliers*); customers (*Coop_customers*); competitors (*Coop_competitors*); consultants (*Coop_consultants*); HEIs (*Coop_HEIs*); government institutions (*Coop_government*); and public research centres (*Coop_centres*) (see Appendix Table A1 for descriptive statistics).

Control variables include a continuous variable (*Size*) to account for the heterogeneity of SMEs. We model exporting activities (*Export*) as a dichotomous variable measuring the share of total sales sold abroad in 2009. Exporting can have a positive impact on cooperation, given that exporters potentially could have a larger network of cooperation partners than do non-exporting firms. Moreover, exporting activities serve as a proxy for firms' foreign competitiveness (Herrera and Nieto, 2008). Furthermore, exporting firms might have more incentive to innovate as a result of competitive pressure on international markets (Busom and Fernández-Ribas, 2008; Czarnitzki and Lopes-Bento, 2013). In addition, the model includes the variable measuring competitive pressure (*Competition*), which is equal to 1 if the firms responded 'Very strong' to the question: "How would you judge the competition in your main market(s)?", and zero otherwise. According to Garcia and Mohnen (2010), firms facing a higher degree of competition could be more likely to be in need of public support.

Following Blundell et al. (1995), our propensity score model includes variables measuring firm-level "quasi fixed effects" (or initial conditions). These initial conditions control for firms' time invariant unobserved effects on innovation, i.e. firms' innovative capacity with respect to technological and non-technological innovations at the beginning of the period covered by the survey (see also Radicic et al., 2014). Firms' quasi fixed effects are modeled with the following variables:

- the dummy variable that measures the resources invested in innovation in 2005 relative to 2009 (*Resources*) (DV = 1 if the firm's response to the question "Five years ago did you devote?" was 'Fewer resources to innovation'; = 0 if 'About the same' or 'More');
- the dummy variable measuring the firms' innovation capacities for introducing product innovation within the industry in 2005 (*Capacity_product*) (DV = 1 for 'Above average' and 'Leading'; = 0 for 'Average' and 'Lagging');
- the dummy variable measuring the firms' innovation capacities for introducing process innovation within the industry in 2005 (*Capacity_process*) (DV = 1 for 'Above average' and 'Leading'; = 0 for 'Average' and 'Lagging');
- the dummy variable measuring the firms' innovation capacities for introducing organizational innovation within the industry in 2005 (*Capacity_org*) (DV = 1 for 'Above average' and 'Leading'; = 0 for 'Average' and 'Lagging');
- the dummy variable measuring the firms' innovation capacities for introducing marketing innovation within the industry in 2005 (*Capacity_marketing*) (DV = 1 for 'Above average' and 'Leading'; = 0 for 'Average' and 'Lagging').

According to Wanzenböck et al. (2013), evaluation studies of innovation policy effects should control for firms' R&D activities. Given the sample coverage of SMEs in traditional manufacturing industries, we control for firms' broader innovation activities by including variables measuring firms' previous innovative capacity (i.e. those referred to as quasi fixed effects). Our modeling strategy conforms to the suggestion in the literature about the failure of innovation input indicators, such as R&D expenditures, to capture innovation activities in SMEs (e.g. Ortega-Argilés et al., 2009; Raymond and St-Pierre, 2010; Santarelli and Sterlacchini, 1990).

Finally, to control for industry heterogeneity, sectoral dummy variables were included for all six industries of interest: automotive, ceramics, leather, metallurgy, textile and food processing. The base category is other industries. In addition, the model includes six country dummy variables for Germany, Italy, France, Portugal, Spain and the Netherlands (with the United Kingdom being the base category).

5 Results of the empirical analysis and discussion

We estimated the impact of public support on various types of cooperation (vertical, horizontal, public-private partnerships). As discussed in Section 3, the first step in matching is to estimate the propensity score. We estimated a logit model, which is the most frequently used model in this line of research (Herrera and Nieto, 2008). The results of the logit model are shown in Table 1.

The results indicate statistically significant effects of two variables capturing initial conditions on treatment assignment, specifically a highly significant impact (at the 1 per cent level) of resources devoted to innovation in 2005 relative to 2009 (*Resources*) and a relatively significant (at the 10 per cent) effect of firms' innovative capacity for process innovation (*Capacity_process*). In addition, exporting activities have a positive impact on programme participation at the 10 per cent level of significance. However, our main focus is not on the estimated coefficients from the logit model, but rather to check whether covariates between matched pairs of treated and untreated firms are balanced given the estimated propensity scores. The literature on matching suggests the inclusion of even those covariates that are statistically insignificant, because their inclusion does not increase bias in subsequent matching estimations (Millimet and Tchernis, 2009). Moreover, our study is limited by a lack of information on the selection process, which means that a large number of covariates should be modelled in the estimation of the propensity score (Millimet and Tchernis, 2009; Steiner et al., 2010).

The algorithm by Becker and Ichino (2002) indicated satisfying balancing properties of the estimated propensity score. Moreover, few observations are lost due to the common support restrictions, which indicates a large overlap of estimated propensity scores among subsidized and non-subsidized SMEs.⁷

Table 2 presents the Average Treatment Effect on the Treated (ATT). With respect to behavioural additionality, the overall results strongly indicate a positive but differential impact of public support. The estimated ATTs are fairly consistent across the three matching estimators. Accordingly, we interpret the mean ATT effects for each outcome variable representing cooperative partners. The ATT for horizontal cooperation (with competitors) is not statistically significant at any conventional level.

⁷These results are available on request.

Table 1. Results of the logit estimation.

Dependent variable: participation in public support programmes in the period 2005-2009.

Variables	Coef.
<i>Size</i>	-0.003 (0.004)
<i>Competition</i>	-0.056 (0.357)
<i>Resources</i>	1.108*** (0.305)
<i>Capacity_product</i>	-0.440 (0.397)
<i>Capacity_process</i>	0.767* (0.465)
<i>Capacity_org</i>	0.791 (0.518)
<i>Capacity_marketing</i>	0.010 (0.495)
<i>Export</i>	0.009* (0.005)
<i>Constant</i>	-1.667*** (0.469)
<i>Industry DVs</i>	Included
<i>Country DVs</i>	Included
No of obs.	264

Notes: Standard errors in parentheses; *** p<0.01, ** p<0.05, * p<0

Conversely, receiving support measures increases the probability of cooperating with consultants, on average, by 18.5 percentage points (p.p.). Moreover, behavioural additionality is found for public-private partnerships. On average, treatment assignment increases the probability of cooperating with HEIs by 31.1 p.p.; of cooperating with government institutions by 28.8 p.p.; and of cooperating with public research centres by 20.0 p.p. The smallest treatment parameters are reported for cooperation with customers (12.1 p.p.) and for cooperation with suppliers (11.6 p.p.). However, both of these treatment estimates are significant at the 10 per cent level, while the latter is statistically insignificant in kernel matching.

Table 2. Average Treatment Effects on the Treated (ATTs) of public support on firms' cooperation for innovation

Outcome variable	NN matching	Kernel matching (Gaussian kernel, bw=0.06)	Double robust estimator	Average ATT estimates
	ATT ^a (Abadie and Imbens SEs) ^b	ATT (bootstrapped SEs) ^c	ATT (robust SEs)	
Cooperation with suppliers (<i>Coop_suppliers</i>)	0.134* (0.074)	0.106 (0.071)	0.108* (0.058)	0.116
Cooperation with customers (<i>Coop_customers</i>)	0.134* (0.074)	0.118* (0.067)	0.111** (0.055)	0.121
Cooperation with competitors (<i>Coop_competitors</i>)	0.000 (0.054)	0.012 (0.053)	-0.030 (0.039)	-0.018
Cooperation with consultants (<i>Coop_consultants</i>)	0.176** (0.069)	0.186*** (0.059)	0.194*** (0.054)	0.185
Cooperation with HEIs (<i>Coop_HEIs</i>)	0.311*** (0.064)	0.328*** (0.064)	0.293*** (0.062)	0.311
Cooperation with government institutions (<i>Coop_government</i>)	0.294*** (0.046)	0.275*** (0.059)	0.294*** (0.041)	0.288
Cooperation with public research centres (<i>Coop_centres</i>)	0.202*** (0.046)	0.207*** (0.047)	0.192*** (0.038)	0.200

Note: ***ATT estimated at the one per cent level of significance; ** ATT estimated at the five per cent level of significance; * ATT estimated at the ten per cent level of significance. ^bAbadie and Imbens (2009) derived a method for variance estimation for NN matching which is applied in this study. ^c Number of replications is 50.

5.1 Sensitivity analysis

As noted in Section 3, the main drawback of matching as an evaluation method is that it controls only for selection on observables. Yet firms' innovative behaviour as well as the selection process can be affected also by unobserved characteristics, such as managerial attitude toward innovation (Busom and Fernández-Ribas, 2008). This unobserved heterogeneity is referred in the evaluation literature as “hidden bias”. The presence of hidden bias indicates a failure of the identifying assumption on unconfoundedness or the selection on observables (CIA). Evaluation literature proposes several tests that can be applied to test for the presence of hidden bias. The results of such tests should be taken with caution, as they cannot directly confirm whether the CIA holds. Rather, they can indicate whether hidden bias arises or not. Testing for unobserved heterogeneity should always complement a propensity

score analysis, as the assumption on unconfoundedness cannot be tested directly (Caliendo and Kopeinig, 2008; Guo and Fraser, 2010; Ichino et al., 2008; Nannicini, 2007).

Sensitivity analysis is not yet common practice in empirical studies on the additionality of innovation policy. Indeed, no previous study on behavioural additionality reports any type of sensitivity analysis. Pearl (2009) points out that researchers often assume that strong “ignorability” (i.e. CIA) holds, because a large number of covariates is included in estimating a propensity score. Yet we argue that more can be done by researchers to address potential biases in the estimation of treatment effects arising from unobserved heterogeneity between treatment and comparison firms: first, the inclusion of “quasi fixed effects” in the estimation of propensity scores may go at least some way to control for otherwise unobserved heterogeneity; and, secondly, we should also examine whether selection on the observable influences included in the model is likely to be satisfied. Although a sensitivity analysis cannot directly test the assumption of selection on observables, it can gauge the level of robustness of empirical findings to hidden bias.

To our knowledge, across the whole range of studies on innovation support programmes, only the study by Alecke et al. (2012) on input additionality reports a sensitivity analysis. However, whereas these authors adopted the Rosenbaum bound approach (Rosenbaum, 2002), we apply a simulation-based sensitivity analysis proposed by Ichino et al. (2008).⁸ The idea behind a simulation-based sensitivity analysis is to determine whether an unobserved confounding binary variable could drive the ATT estimates to zero, under the assumption that this variable simultaneously affects a treatment assignment and the outcome variable (Nannicini, 2007). Sensitivity of the estimated results with respect to hidden bias would indicate that the results are not robust (Becker and Caliendo, 2007; Caliendo and Kopeinig, 2008).

A simulation-based sensitivity analysis starts with the choice of four parameters p_{ij} defined as:

⁸Our choice to apply the simulation-based sensitivity analysis reflects the following considerations. The Rosenbaum bound approach can only be applied after NN matching without replacement and stratification, while the simulation-based approach can be applied after kernel matching, among other estimators. On the one hand, there are reasons why we do not apply NN matching in this study. The literature on matching estimators suggests that NN matching without replacement should be used when there is a large control group, and this condition is not met in our sample (Stuart, 2010). In addition, the estimator might yield poor matches, as it does not match propensity scores of treated and non-treated units with minimum distance. On the other hand, kernel matching is in general preferred to NN matching with replacement (Morgan and Harding, 2006). Frölich (2004) used Monte Carlo simulations to test how various matching estimators perform in small samples, and found that kernel matching performed better than NN matching. In conclusion, our choice of matching estimator determined our application of simulation-based sensitivity analysis.

$$p_{ij} \equiv P(U = 1|T = i, Y = j) = P(U = 1|T = i, Y = j, X) \quad (3)$$

Where U denotes the binary confounding variable, and $i, j \in \{0,1\}$, where i denotes the probability of treatment assignment and j is the probability of cooperating for innovation (in our study). Combining i and j gives four possibilities for $U=1$ (p_{00} , for example, denotes the probability that $U=1$ for non-treated firms that do not cooperate with cooperative partners, i.e. the outcome variable is equal to zero). Each firm in the sample is assigned a value of U depending on parameters p_{ij} . The simulated confounding variable U is treated like other observed covariates X , i.e. it is included in the propensity score equation, which is then used for the computation of the ATT estimate. The result of sensitivity analysis is the point estimate of the ATT that is robust to hidden bias. If the simulated ATT is close the baseline ATT estimate derived under the CIA, then the baseline estimate is likely to be robust to unobserved heterogeneity (Nannicini, 2007).

Table 3 reports the results of a sensitivity analysis for the simulated ATT estimates from kernel matching. Besides the simulated ATT estimates, Table 3 reports the outcome and selection effects. The former is the average odds ratio of U for cooperating non-subsidized firms, whereas the latter is the average odds ratio of U for subsidized firms. These effects should be interpreted as follows. For instance, for the outcome variable cooperation with suppliers, the unobserved confounder U would increase the probability of having Y_1 (cooperating with suppliers) above the mean, respectively, by a factor greater than 5 (the outcome effect) and by a factor slightly less than 8 (the selection effect). Most important, Table 3 shows that the simulated ATT estimates are very close to the baseline estimates presented in Table 2. This indicates that, even for large outcome and selection effects, the simulated treatment effects do not deviate from the baseline effects. Consequently, our sensitivity analysis suggests that deviations from the underlying conditional independence assumption (CIA) are highly unlikely to occur.

Table 3. Results of the simulated-based sensitivity analysis

Outcome variable	Kernel matching	Outcome effect	Selection effect
	Simulated ATT ^a (bootstrapped SEs)		
Cooperation with suppliers	0.106 (0.071)	5.404	7.982
Cooperation with customers	0.118* (0.067)	5.945	8.248
Cooperation with competitors	0.012 (0.053)	1.69e+14	11.004
Cooperation with consultants	0.186*** (0.059)	8.950	9.754
Cooperation with HEI	0.328*** (0.064)	7.307	9.433
Cooperation with government institutions	0.275*** (0.059)	1.53e+32	11.773
Cooperation with public research centres	0.207*** (0.047)	1.31e+35	12.318

Notes: ^a *** ATT estimated at the one per cent level of significance; ** ATT estimated at the five per cent level of significance; * ATT estimated at the ten per cent level of significance.

6 Conclusions and policy implications

In this study we evaluated the innovation policy effects on cooperation for innovation among SMEs. This line of investigation refers to cooperation additionality, as a subcategory of the broader concept of behavioural additionality. Our study contributes to the existing empirical evidence by focusing on behavioural additionality in SMEs. Empirical results obtained from propensity score matching estimators report a positive but heterogeneous impact of public support on SME cooperation for innovation. Overall, the largest treatment parameters are estimated for public-private partnerships, followed by cooperation with consultants. Furthermore, small and borderline significant treatment effects are found for vertical cooperation with suppliers and customers. Finally, there is no behavioural additionality for cooperation with competitors (vertical cooperation). The findings from this study corroborate empirical evidence from previous studies on behavioural additionality, insofar as the largest effects are found for cooperation with public institutions (HEIs, government institutions and public research centres) rather than with other firms (customers, suppliers and competitors).

Our study also uniquely reports results of a simulation-based sensitivity analysis, whose results suggest that the programme effects are not likely to be sensitive to unobserved

heterogeneity between treatment and comparison firms. Although we are able to include a relatively small number of covariates in the estimation of the propensity score, these encouraging results of sensitivity testing are consistent with our intention to better control for sources of otherwise unobserved heterogeneity by the inclusion – novel in matching estimation – of “quasi fixed effects”. Moreover, by conducting sensitivity analysis, our study follows the best practice in applying matching estimators. We hope to encourage further studies that investigate various categories of additionality (input, output and behavioural) by applying matching estimators together with sensitivity analysis. Such a broadening of research activity would give rise to a body of empirical evidence on the likelihood of unobserved heterogeneity in this field of research.

In summary, our empirical findings show that SMEs are more likely to respond to public support by increasing either their cooperation with public institutions such as HEIs, government agencies and public research centres, than by establishing and maintaining cooperative associations with customers, suppliers and competitors. These findings provide support for the hypothesis advanced in Section 2. Furthermore, following the discussion in Section 2.1, acquiring external knowledge through cooperation could be subject to cooperation failure. In this case, compared to cooperation with other firms, increased cooperation with public institutions may be facilitated by greater trust insofar as these institutions are unlikely to appropriate the firm’s intellectual property. SMEs are less likely to utilize patents and other formal mechanism of the IP protection (Leiponen and Byma, 2009), which implies that mutual trust is the critical factor in successful cooperation for innovation. According to Clarysse et al. (2009), with respect to types of cooperative partners, the risk of cooperation failure is particularly high for cooperation with competitors, and our results suggest that innovation policy instruments might not be able to mitigate this risk. This issue deserves further attention from both practitioners and policy-makers. For example, to increase the effectiveness of public support for cooperation between firms – including customers and suppliers – policy makers should place particular emphasis on measures designed to attenuate cooperation failures (Zeng et al., 2010).

Our study supports three policy implications. First, participation in public support measures reduces barriers to cooperation in manufacturing SMEs – however cooperation failure that could pertain to cooperation with competitors (horizontal cooperation) is unlikely to be minimized by innovation policy instruments. Other policy instruments might complement public subsidies, such as improving the absorptive capacity of SMEs and establishing technology transfer offices (Busom and Fernández-Ribas, 2008). Second, our

study found support for Georghiou's (2002) hypothesis of the substitutability of input and output additionality with behavioural additionality. In other words, public support might not induce larger output additionality (as reported in Radicic et al., 2014), but it might increase the probability of cooperating for SME innovation. Finally, as public support programmes induce behavioural additionality among SMEs in manufacturing industries that are generally not R&D intensive, policy measures focused on R&D intensive firms should expand their scope to include this category of SMEs. This policy recommendation is consistent with Wanzenböck et al (2013), who reached a similar conclusion in the context of the Austrian transport sector, and with Clarysse et al. (2009) who report larger behavioural additionality for less R&D intensive SMEs than for high R&D intensive large firms.

In conclusion, empirical investigation into behavioural additionality is still in its nascent years. Our analysis is the first to investigate the impact of public innovation measures in SMEs. However, available data does not allow for assessing public effectiveness on cognitive capacity additionality (Busom and Fernández-Ribas, 2008; Fier et al., 2006). Furthermore, the lack of longitudinal data inhibits exploration of the medium-to-long-run effects of programme participation on cooperative behaviour (Busom and Fernández-Ribas, 2008). And, finally, whilst we do not have data on the number of cooperative partners, it would be interesting to explore whether additionality of a support programme would be affected by the breadth of cooperative partnerships.

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Appendix A. Table A1: Descriptive statistics*

Variables	Mean	Standard deviation	Minimum	Maximum
<i>Participation</i>	0.451	0.499	0	1
<i>Size (employees)</i>	35.208	44.723	0	230
<i>Micro firms</i>	0.330	0.471	0	1
<i>Small firms</i>	0.432	0.496	0	1
<i>Medium-sized firms</i>	0.238	0.427	0	1
<i>Competition</i>	0.231	0.422	0	1
<i>Export (share of total sales)</i>	19.670	29.956	0	100
<i>Resources</i>	0.371	0.484	0	1
<i>Capacity_product</i>	0.265	0.442	0	1
<i>Capacity_process</i>	0.208	0.407	0	1
<i>Capacity_org</i>	0.129	0.336	0	1
<i>Capacity_marketing</i>	0.163	0.370	0	1
<i>Coop_suppliers</i>	0.326	0.470	0	1
<i>Coop_customers</i>	0.337	0.474	0	1
<i>Coop_competitors</i>	0.083	0.277	0	1
<i>Coop_consultants</i>	0.235	0.425	0	1
<i>Coop_HEIs</i>	0.311	0.464	0	1
<i>Coop_government</i>	0.163	0.370	0	1
<i>Coop_centres</i>	0.125	0.331	0	1
<i>Leather industry</i>	0.042	0.200	0	1
<i>Ceramic industry</i>	0.072	0.259	0	1
<i>Textile industry</i>	0.114	0.318	0	1
<i>Mechanical/metallurgy industry</i>	0.303	0.460	0	1
<i>Automotive industry</i>	0.110	0.313	0	1
<i>Food processing industry</i>	0.163	0.370	0	1
<i>Other traditional manufacturing industries</i>	0.197	0.398	0	1
<i>Spain</i>	0.186	0.390	0	1
<i>France</i>	0.098	0.299	0	1
<i>Germany</i>	0.110	0.313	0	1
<i>Italy</i>	0.163	0.370	0	1
<i>Netherlands</i>	0.098	0.299	0	1
<i>Portugal</i>	0.061	0.239	0	1
<i>United Kingdom</i>	0.284	0.452	0	1

* Means are proportions of the sample firms unless otherwise specified. Full definitions of each variable are given in the text.