

R&D programmes, policy mix, and the “European Paradox”: evidence from European SMEs

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Abstract

Using a sample of SMEs from 28 European countries, this study evaluates the input and output additionality of national and EU R&D programmes both separately and in combination. Accordingly, we contribute to understanding the effectiveness of policy mix, in this case of innovation policy from the perspective of multi-level governance. Empirical results are quite different for innovation inputs and innovation outputs. For innovation inputs, we found positive treatment effects from both national and EU programmes separately as well as complementary effects for firms supported from both sources relative to firms supported only by national programmes. For innovation outputs, we report no evidence of additionality from national programmes and cannot reject crowding out from EU programmes. However, crowding out from EU support is eliminated by combination with national support. These findings have policy implications for the governance of R&D policy and suggest that the European Paradox – success of EU support in promoting R&D inputs but not commercialisation – is not yet mitigated.

Keywords: R&D support; SMEs; Policy mix; Input and output additionality; European Paradox

1. Introduction

Innovation policy has taken centre stage among policy makers in the European Union (EU) (Edler et al. 2012a; European Commission 2010). Small and medium-sized enterprises are regarded as the engine of growth in the European economy (European Commission 2013). Correspondingly, policy makers not only recognize the importance of innovation and its public support, but increasingly recognize the relevance of evaluating the impact of support measures

(Edler et al. 2012b), including for SMEs (Radicic et al. 2015). The complexity of innovation policies is actuated by the broadening of policy domains. More specifically, implementation of innovation policies is practically conducted at different administrative levels: local; regional; national; and supra-national (European Union) (Magro and Wilson 2013; Vītola 2015). The implication is that a wide range of policy measures implemented at all administrative levels interact with one another (Magro and Wilson 2013). Given the interaction between various innovation instruments implemented at different administrative levels but in the same geographical area, difficulties arise in evaluating individual policy measures. Therefore, there is an emerging need for systemic evaluation, which takes into account interactions and interdependencies of modern innovation policies (Magro and Wilson 2013; Vītola 2015): “... an evaluation approach needs to be able to cover the interplay of measures as well as individual measures” (Edler et al. 2012b, p.7).¹

This study evaluates the individual and joint impacts of national and international (EU) R&D programmes on innovation in European small and medium-sized enterprises (SMEs). In assessing policy effects, the study adopts the approach introduced in Czarnitzki and Lopes-Bento (2014) and Guerzoni and Raiteri (2015) in relation to the presence of “hidden treatment”. Namely, firms could be recipients of more than one R&D and innovation policy. In this setting of multi-treatments, individual programmes’ effects might be overestimated when the interactions between different innovation policies are not addressed (Guerzoni and Raiteri 2015). However, interactions between policies and policy instruments have received little attention with respect to either theory development or empirical investigation (Cunningham et al. 2013a). To address the issue of hidden treatment, our empirical strategy takes into account the interaction between national and EU R&D programmes. Naturally, other innovation policy instruments, particularly from the demand-side (such as public procurement and innovation vouchers), could affect firms’ innovation inputs and outputs (Guerzoni and Raiteri 2015). However, our survey data does not contain information on other potential hidden treatments, which is why we focus on the interplay between national and EU R&D programmes. In evaluating the interplay between national and EU R&D programmes, we contribute to the scant empirical literature on innovation “policy mix” (Vītola 2015), defined as the balance and interactions among policy interventions (OECD 2010).

¹ Martin (2016) identifies four major trends in our thinking about innovation: from the linear model to systems of innovation; from national to multi-level governance; from individual research to networking and cooperation; and from individual policies to policy mixes. Our empirical strategy is part of this most recent trend.

The central question within the evaluation debate is related to the effectiveness of public subsidies, i.e. whether firms increase their innovative efforts as a result of public intervention (additionality) or substitute their private investment with public funding (crowding out) (David and Hall 2000; David et al. 2000). The type of additionality effect is contingent on the phase of the innovation process that is affected by the provision of public support: input additionality refers to whether public support measures induce larger investment in R&D and other innovation inputs relative to firms' private funding in the absence of public support programmes; output additionality occurs when public support results in larger innovation output, such as increasing patent applications, and/or the introduction of technological and non-technological innovations; and, behavioural additionality arises when policy instruments induce changes in firms' innovative behaviour (Falk 2007; OECD 2006a). In line with an increasing demand for systemic evaluation, one recommendation is that all three types of additionality should be explored in an integrated approach (Gök and Edler 2012; Margo and Wilson 2013). To reflect this emerging practice, the focus of this study is on assessing both input and output additionality. We are not able to investigate behavioural additionality, because of lack of information in the data.

Finally, SMEs innovate differently than do large firms. Yet very few studies examine the effectiveness of public support measures on innovation in the context of SMEs. This study aims to fill this gap by examining the impact of national and EU R&D policy support on SME innovation. Drawing on a sample of European SMEs, we utilize a matching estimator to estimate treatment effects of R&D programmes on innovation inputs and outputs. Our second contribution is to evaluate whether public support measures are complementary in supporting different phases of innovation processes (innovation inputs and outputs) and at different governance levels. So far, only the study by Czarnitzki and Lopes-Bento (2014) tackled these issues empirically, although not in the context of SMEs. The third contribution is that our study contributes to the evidence base on the “European paradox” (European Commission 1995) by showing that it applies to SMEs in particular; we find that EU support for SMEs promotes input additionality but not output additionality.

The study is organized as follows. The next section discusses the emergence of policy mix and a consequent need for systemic evaluation, followed by the review of empirical studies on input and output additionality. Section 3 provides an overview of the matching estimator and the dataset used in the study and specifies the empirical model. Section 4 presents and discusses empirical findings. Section 5 concludes.

2. Theoretical considerations and literature review

2.1. Policy mix and systemic evaluation

Economic theory advances two complementary rationales for public intervention in the domain of innovation: the market failure rationale; and the evolutionary, system-failure rationale. From the late 1950s onwards, the market failure rationale has provided a basis for policy instruments designed either to lower the costs of private R&D and innovation activities or to raise the payoff from knowledge creation (Smith 2000). The second, evolutionary system-failure rationale broadened the scope of public intervention by addressing failures in the functioning of innovation systems (Arnold 2004; Smith 2000). Whilst the market-failure rationale emphasizes the importance of investing in science and technology, the evolutionary-systemic rationale focuses on the interaction of organizations and institutions within systems of innovation. Therefore, the innovation policy domain is characterized by the existence of complementary policy rationales, accompanied by a complementary mix of policy instruments. From the perspective of current innovation policy, both rationales are valid and contribute to policy design and implementation (Bleda and del Río 2013; OECD 1998). To reflect the widening of policy rationales and a proliferation of various policy instruments, the concept of the innovation “policy mix” has recently emerged (Belitz and Lejpras 2016; Flanagan et al. 2011; OECD 2010).

Public measures aimed at supporting and promoting innovation are divided into two broad categories: supply-side public measures; and demand-side measures. Boekholt (2010, p. 334) defines a policy instrument as 'a government measure or programme that aims to change the behaviour and actions of the actors involved in the whole process from generating new ideas into innovative market introductions and solutions'. Supply-side measures stem from the first-generation linear innovation models, and have been the dominant category of public intervention in the domain of innovation since the market-failure rationale was advanced in theory and practice (Edler and Georghiou 2007). The second generation of demand-pull innovation models shifted the focus to the demand side of the innovation process but, at the same time, ignored the role of firms' technological capabilities in the innovation process (Nemet 2009). Demand-side public measures were designed after the formalization of the third-generation interactive or coupling innovation models, bringing together the technology-push and the demand-pull arguments (Kline and Rosenberg 1986).

As innovation policies evolved from one generation to another, new instruments were launched but existing instruments were seldom abolished (Boekholt 2010; Margo and Wilson

2013). That is one of the reasons why nowadays a large number of public measures exists. Consequently, the evolution of policies related to innovation resulted in the shift in policy-making focus, from identifying the best policy instruments to formalizing a portfolio of instruments that will have a joint positive impact on innovation. A policy mix can be defined as 'the combination of policy instruments, which interact to influence the quantity and quality of R&D investment in public and private sectors' (Boekholt 2010, p. 353). Finding a holistic solution based on the policy mix is not an easy task, as the synergetic effects of policy instruments might amplify or cancel individual positive effects. The complexity of innovation policies stemming from different rationales, objectives and dimensions makes system evaluation rather difficult. In that sense, evaluation of innovation policy is underdeveloped relative to innovation theory (Magro and Wilson 2013). This is in line with the conclusion in Flanagan et al. (2011, p.711): 'A key role for innovation policy studies should be to highlight the trade-offs and tensions inherent in any policy mix and to promote open debates about them.'

The European Commission, in its Green Paper on Innovation (European Commission 1995), identified the "European Paradox" as the main weakness of the innovation system of the European Union relative to those of the US and Japan (Dosi et al. 2006; Hammadou et al. 2014). The paradox refers to the inability of the EU to transform '*...the results of technological research and skills into innovations and competitive advantage*' (European Commission 1995, p.5). Following Hammadou et al. (2014), the European Innovation System is effective in producing basic research, stimulated mainly by public spending on R&D, but less effective in producing innovation outputs, whether from the technological aspect or from the commercial aspect. In other words, there is an innovation gap insofar as public support spurs innovation inputs (R&D) but not innovation outputs (OECD 2012). The traditional, supply-side, policy measures have been a dominant type of R&D and innovation policy across EU Member States and at the EU level since the 1950s. However, these measures have not been successful in mitigating the European Paradox (OECD 2010; 2012). Nowadays, EU policy makers are putting more emphasis on demand-side measures, predominantly public procurement, hoping that the rather disappointing effectiveness of the supply-side measures will be complemented by the effects of demand-side interventions (OECD 2010; 2012).

2.2. Types of additionality

Additionality refers to an increase in firms' innovation activity as a result of public intervention. Conversely, crowding out occurs when firms replace their private investment in

innovation with public funding (David and Hall 2000; David et al. 2000). Crowding out is further categorized into full crowding out (firms' private funding completely substituted by public investment) and partial crowding out (firms reduce their private investment in innovation, but not to the extent of public funding received) (Aerts and Schmidt 2008; Gonzáles and Pazó 2008). A partial crowding-out effect can only be hypothesised when the amounts of subsidies are available, which is rare in innovation studies (Radicic et al. 2015). Hence, most studies are limited to testing the hypothesis of additionality versus a full crowding out effect. In this respect, our study is not an exception, as the amount of subsidies is not available in our dataset.

An important shortcoming of input additionality is its focus on the allocation of resources, without exploring the effects of public intervention on innovation outputs and changes in firms' innovative behaviour (Antonioli and Marzucchi 2012). For this reason, this study assesses both input and output additionality, thus contributing to a more systematic evaluation of R&D and innovation policy. Regarding output additionality, innovation output indicators can be categorized into two groups: intermediate (direct) innovation outputs (such as patents and publications); and indirect innovation outputs, such as the introduction of product and process innovations and the share of sales from new products and/or processes (i.e. innovative sales) (Clarysse et al. 2009).

2.3. Literature review

Arvanitis (2013), in line with Cerulli (2010), notes that there is no commonly accepted theory of public support to explain the selection process, because the process itself is specific and hinges on objectives set by the government. This could be the reason why David and Hall (2000), David et al. (2000) and Dimos and Pugh (2016) suggest that, theoretically, both treatment effects (additionality and crowding out) are possible, thus leaving resolution to empirical analysis.

Input additionality is the subject of the largest number of studies (Clarysse et al. 2009; Cunningham et al. 2013b). Notwithstanding a large volume of empirical studies, overall evidence about input additionality remains inconclusive; evidence of a positive treatment effect seems to prevail (García-Quevedo 2004; Zúñiga-Vicente et al. 2014), although this is typically very small (Radicic et al. 2015). Focusing on the differential impact of public support by firm size, several studies (e.g. Alecke et al. 2012; Gonzáles et al. 2005; Gonzáles and Pazó 2008;

Herrera and Sánchez-González 2012) provide evidence that input additionality is likely to be found in SMEs.

Fewer studies investigate output additionality, although their number has grown in recent years (Clarysse et al. 2009; Cunningham et al. 2013b). Most studies report positive output additionality. In terms of how innovation outputs are operationalized, propensity to patenting or patent counts, as a measure of intermediate output, and innovative sales, as a measure of market success of innovation, are most frequently utilized (e.g. Arvanitis et al. 2010; Herrera and Sanchez-Gonzales 2012; Hewitt-Dundas and Roper 2010; Hussinger 2008). Focusing specifically on SMEs, Foreman-Peck (2013) assesses output additionality in manufacturing and service UK SMEs. The study reports that public support increases the probability of introducing product or process innovations in UK SMEs.

In the context of SMEs, three studies have adopted an integrated approach to policy evaluation by assessing more than one type of additionality. First, Hottenrott and Lopes-Bento (2014) investigate whether a direct financial support for R&D induces input and output additionality in Flemish SMEs. The results from caliper matching indicate positive additionality effects on both innovation input and output indicators. Similarly, Alecke et al. (2012) apply kernel matching to assess the effectiveness of public support among manufacturing and service SMEs in East Germany. The study reports input and output additionality effects, implying that subsidized firms are more R&D intensive than non-subsidized firms and the probability of patent application is higher in subsidized than in non-subsidized firms. Finally, Czarnitzki and Delanote (2015) report input and output additionality among independent, young SMEs in high-tech sectors in Germany. Their results indicate the largest treatment effects for this group of firms, relative to low-tech young firms and non-independent counterparts. Thus, they conclude that the preferential treatment that policy makers provide to this category of firms is justifiable.

Another dimension of policy mix is the multi-level governance of R&D and innovation programmes across Europe. Policy instruments in a policy mix could: i) be complementary; ii) be substitutes; or iii) not interact (Magro and Wilson 2013; Borrás and Edquist 2013; Cunningham et al. 2013a; OECD 2010; Vītola 2015). Moreover, Flanagan et al. (2011) and Cunningham et al. (2013a) identify four dimensions of policy mix interactions: policy space (when several policy instruments target the same group of firms); governance space (between different levels of governance); geographical space; and time. Our study fits into the second dimension of governance space, as our aim is to assess the interplay in policy mix at two governance levels: national and international. Across the EU, innovation policies are

implemented at regional, national and international levels (Magro and Wilson 2013; Vītola 2015). Multi-level governance or coordination of policies at different administrative levels is underdeveloped, although their interdependence is often evident (OECD 2010).

There are three main sources of international R&D programmes in the European Union: a) the Research Framework Programmes; b) the Cohesion Fund; and c) the Competitiveness and Innovation Framework Programme (CIP) (Czarnitzki and Lopes-Bento 2014). The Research Framework Programmes (FPs) are focused on different thematic aspects and objectives with a common objective of fostering technological competitiveness in Europe. There have been eight editions up to date (FP1 to FP7 covering the period from 1984 to 2013, while FP8 is termed Horizon2020 and is effective from 2014 to 2020). In recent years, the main goal of FPs is the establishment of the European Research Area (Scherngell and Barber 2011). The Cohesion Fund Policy is a policy instrument designed to implement regional policy in the EU. In recent years, the emphasis has been placed on supporting depressed regions (Czarnitzki and Lopes-Bento 2014) in order to reduce economic and social disparities between Member States. Finally, the CIP covered the period 2007-2013 with SMEs as the main target. It consisted of three operational programmes focusing on innovation in SMEs (the Entrepreneurship and Innovation Programme – EIP), the use of information and communication technologies (ICTs) (the Information Communication Technologies Policy Support Programme – ICT-PSP), and on energy efficiency (the Intelligent Energy Europe Programme - IEE). This Instrument has been replaced by the Programme for the Competitiveness of Enterprises and SMEs (COSME), which runs from 2014 to 2020. In addition to EU programmes, there are a wide range of support programmes at national, regional and local levels.²

Empirical evidence on potential complementarity effects between funding provided from different governance levels is particularly scarce (Vītola 2015). So far, only Czarnitzki and Lopes-Bento (2014) explored this issue empirically. They have taken into account what Guerzoni and Raiteri (2015) termed hidden treatment by distinguishing between national and EU funding sources, and estimating their individual as well as joint impact on innovation inputs and outputs in German firms. Our approach is similar to Czarnitzki and Lopes-Bento (2014) with respect to the treatment of multi-level governance. The main differences are country

²Although restricted in scope to SMEs in traditional manufacturing industries, the FP7 GPrix project reported more than 400 innovation support programmes across the EU without any claim to being exhaustive (Radicić et al. 2015).

coverage (we have data for 28 European countries), our focus on SMEs and the choice of the matching estimator.

Concerning the country coverage, empirical studies are usually limited to one country, which restricts international comparison and consistent policy recommendations. Consequently, few studies evaluate the effectiveness of public support measures in more than one country (see e.g. Aerts and Schmidt 2008; Czarnitzki and Lopes-Bento 2012; Hewitt-Dundas and Roper 2010), and even those that cover several countries are not specifically concerned with SMEs. Thus, by analysing firms from 28 European countries, our study contributes to a more comprehensive policy evaluation regarding this heterogeneous group of firms. Although the sample is too small to analyse each country separately, empirical findings for the whole sample of European SMEs provide at least tentative evidence on the effectiveness of national and international R&D programmes in stimulating SME innovation.

Very few studies report empirical findings on the effectiveness of public support when the amounts of public support are available. Dai and Cheng (2015) analyse how public support affects innovation inputs in Chinese manufacturing firms. The study does not distinguish between national and international sources of subsidies. Their empirical findings reveal a non-linear relationship between R&D subsidies and innovation inputs. More precisely, when the amount of public subsidy is beyond the optimal level, public support induces either partial or full crowding-out effects. Marino et al. (2016) also report a non-linear relationship between public subsidies and private R&D expenditure in French firms. Empirical evidence from a dose-response matching estimator indicates a crowding-out effect for medium-high levels of public subsidies. To our knowledge, no study explores output additionality in the case when doses of treatment are known.

2.4. Hypotheses

Given that the theoretical considerations about the effectiveness of public support on innovation inputs predict that both additionality and crowding-out effects are feasible and that empirical evidence on input additionality is mixed, we posit the following alternative hypotheses regarding the effectiveness of national and EU R&D programmes.

H1A (H1B): National R&D programmes have a positive (negative) effect on innovation inputs (R&D employment and R&D expenditure).

H2A (H2B): EU R&D programmes have a positive (negative) effect on innovation inputs (R&D employment and R&D expenditure).

Concerning the joint impact of both national and EU R&D programmes, theory suggests a higher joint impact than the impact of either national or EU programmes. Thus, we posit.

H3: The joint impact of national and EU R&D programmes on innovation inputs is larger than the impact of either national or EU R&D programmes in isolation.

With respect to relative effects, the theoretical framework is lacking, while empirical evidence is scarce (the exception is Czarnitzki and Lopes-Bento 2014). Consequently, instead of hypotheses, we identify research questions.

- What is the impact of EU programmes on innovation inputs relative to national programmes?
- What is the impact of both national and EU programmes on innovation inputs relative to national programmes only?
- What is the impact of both national and EU programmes on innovation inputs relative to EU programmes only?

Each of these hypotheses and research questions regarding innovation inputs has its counterpart regarding innovation outputs.

H4A (H4B): National R&D programmes have a positive (negative) effect on innovation outputs (patents and innovative sales).

H5A(H5B):EU R&D programmes have a positive (negative) effect on innovation outputs (patents and innovative sales).

H6: The joint impact of national and EU R&D programmes on innovation outputs is larger than the impact of either national or EU R&D programmes in isolation.

And, with respect to relative effects: What is the impact of EU programmes on innovation outputs relative to national programmes? What is the impact of both national and EU programmes on innovation outputs relative to national programmes only? What is the impact of both national and EU programmes on innovation outputs relative to EU programmes only?

3. Methodology

3.1. Estimation of the Average Treatment on the Treated (ATT) effect

Treatment assignment into support measures should be regarded as endogenous due to selection bias arising in the process of application and distribution of public measures, because

either: a) firms self-select themselves into programmes; and/or b) programme agencies adopt a “picking-the-winner” strategy during the selection process (Antonioli and Marzucchi 2012; Cerulli 2010; David et al. 2000; Grilli and Murtinu 2011). The corollary is that the effect of programme participation – the Average Treatment on the Treated (ATT) effect – must be estimated. In essentials, we follow the most common approach in this kind of research, which is to match by means of propensity scores supported (“treated”) firms to unsupported (“untreated”) firms with similar characteristics – which thus constitute a comparison group³ – and then to estimate the difference between some outcome of interest (Y_1) for participating firms and the outcome for non-participating firms (Y_0) (Cerulli 2010).⁴ To safely attribute the estimated difference to participation, the treated firms must be similar to the untreated firms in all respects except for participation. In turn, this depends on two identifying assumptions: the conditional independence assumption (CIA), or selection on observables, which posits that the outcome in the case of no treatment (Y_0) is independent of treatment assignment (T), conditional on covariates X (Imbens 2004; Imbens and Wooldridge 2009); and the overlap or common support condition, whereby the estimated propensity scores take positive values (Heckman and Vytilacil 2007). Regarding the selection of covariates X , the literature suggests that all observed variables that simultaneously affect treatment assignment and the outcome should be included in the estimation of propensity scores (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, 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.

We employ the inverse probability of treatment weighting regression adjustment (IPWRA) estimator. The IPWRA estimator belongs to a group of matching estimators that have the double-robust property. Double robustness implies that either the treatment model or the outcome model (or both) have to be correctly specified for the estimator to produce consistent treatment effects (Hirano et al. 2003). The main advantage of the IPWRA estimator is its double robust property. If either the propensity score model (the outcome model) or the treatment model is correctly specified, then this estimator will yield treatment effects with a lower bias than will other estimators that are not characterized by the double-robustness property. Busso et al. (2014) conducted a Monte Carlo simulation of the finite sample properties of a range of

³ We prefer the term “comparison” to “control” group, because the latter implies random allocation.

⁴ In effect, the matching approach estimates the difference between firms in two states that cannot be observed simultaneously: the participation state; and the counterfactual state of non-participation.

matching and reweighting estimators – which include the IPWRA – in the estimation of ATTs. Their findings support our use of the IPWRA: first, we use normalised reweighting, which exhibits overt bias of the same magnitude as pair matching but much smaller variance; second, their findings suggest that normalised reweighting outperforms matching estimators when overlap is good, which is the case in our study (see Figure 1.).

The estimator consists of three steps. First, the treatment model estimates, for each firm in the sample, the propensity score, which is the probability for each firm of participation (“treatment assignment”). Given that we evaluate multiple treatment effects, the propensity scores are estimated by a multinomial logit model, incorporating all four treatment levels: neither national nor EU R&D programmes; only national; only EU; and both. The choice of the model is motivated by the nature of our treatment variable, which has more than two outcomes with no natural ordering. The propensity scores enable firms to be matched within each treatment level. Second, regressions are estimated by ordinary least squares (OLS) for each of our innovation variables in categorical form – *R&D employment*, *R&D expenditure* and *Innovative sales* – and by probit for our binary innovation variable *Patents*, in which the inverse of the estimated propensity scores are used as weights on covariates X and our treatment dummies.⁵ Third, from each of these regressions, the ATT effect is computed as the difference between the treatment and control group in the weighted averages of the predicted outcomes for each firm (for technical details see Wooldridge 2010). To take into account that various innovation support programmes are undertaken simultaneously, we estimate treatment effects in the multi-treatment context. Following Czarnitzki et al. (2007) and Guerzoni and Raiteri (2015), ATT effects are estimated for each treatment level, whereby treatment equal to zero denotes the absence of participation in either national or EU R&D programmes. This three-step approach provides consistent estimates given the underlying assumption of the independence of the treatment from the predicted outcomes once covariates are modelled in steps 1 and 2. We report valid standard errors (of the Huber/White/sandwich type) which take into account that the estimates are computed in a three-step approach (Emsley et al. 2008).

3.2. Data

⁵ Strictly, OLS estimation is for continuous variables, whereas our categorical variable (with four or six ordinal categories) are treated as if they constitute a continuous variable. In this we follow established practice in other areas of economics – e.g. in the “economics of happiness”, the typical dependent variable is ‘life satisfaction, measured on an ordinal scale from 1 to 7... and is treated as a cardinal variable, as is common in the literature’ (Piper, 2015, p.56).

The dataset used in the analysis was gathered in 2010 within the MAPEER project commissioned by the European Commission's DG-Research.⁶ The survey questionnaire covered the period 2005-2010. The sample includes 763 SMEs from 28 European countries. The survey was targeted to the population of SMEs with fewer than 250 employees and an annual turnover of less than 50 million Euros (EU definition of SMEs – Article 2 of the Annex of Recommendation 2003/361/EC) (European Commission 2005). Within the group, micro-sized firms are defined as those with fewer than 10 employees, small firms with more than 10 and fewer than 50 employees and medium-sized firms with more than 50 and fewer than 250 employees. Due to missing values, the final sample consists of 671 SMEs (324 micro firms, 218 small firms and 129 medium-sized firms). Given the small number of firms from individual countries, they were grouped into four categories based on the European Innovation Scoreboard (European Commission 2011) (see Appendix A.1 for the list of countries in each category):⁷

- 'Innovation leaders', countries whose innovation performance is well above the EU27 average. Our sample consists of 115 SMEs operating in four countries from this category.
- 'Innovation followers', countries with performance close to the EU27 average (189 firms in ten countries);
- 'Moderate innovators', countries whose performance is below that of the EU27 average (260 firms in nine countries); and
- 'Modest innovators', representing countries whose performance is well below that of the EU27 average (107 firms in five countries).

As data are self-reported, common method variance, arising from the measurement method, could bias the estimates due to systematic measurement error (Podsakoff and Organ 1986). To check the internal validity of our data, we conducted Harmon's one-factor test (Podsakoff and Organ 1986). The test encompasses an explanatory factor analysis of all independent variables by using unrotated principle component factor analysis. When the common method bias is

⁶ For detailed information about the project, see http://cordis.europa.eu/project/rcn/93511_en.html.

⁷ The European Innovation Scoreboard publishes the average innovation performance of EU member states based on a composite indicator, consisting of 24 individual indicators. Innovation performance of each Member State is then compared to the average innovation performance of 27 EU Member States. For the purpose of this study, we use the Innovation Scoreboard from 2011, as it refers to innovation performance in the years 2009/2010. Moreover, as Bosnia and Herzegovina is the only country in the sample which is not a member state, its innovation performance was evaluated to be modest, based on its low Gross Domestic Expenditure on R&D of 0.02 percent of GDP for 2009 (UNESCO data, <http://data.uis.unesco.org/>).

unlikely to occur, the first unrotated factor (i.e. the factor accounting for the largest share of the variance of the independent variables) should account for less than 50 per cent of the total variation in the other explanatory variables within the model. In our model, the first factor accounts for around 12 per cent of total variation, which suggests that common method bias raises no great concern in our model.

The survey sample was obtained by the EU Framework 7 MAPEER project. Project members anticipated the practical difficulty – arising from previous experience – that it would be difficult to obtain large numbers of questionnaire responses from SMEs. Interview evidence gathered in the course of the project yielded several predictable findings in this regard, including: cultural barriers, especially among owners and managers of traditional-sector SMEs; owners and managers are too busy, typically having nobody to whom to delegate non-essentials, which include completing questionnaires; and SME owners and managers dislike paperwork, including questionnaires.⁸ One corollary of the anticipated low response rate was the danger that a simple representative sample of SMEs would include insufficient programme participants for useful analysis. Accordingly, the project used a species of stratified sampling; i.e. a random sample biased in a deliberate way towards programme participants. To this end, a two-fold approach was implemented by project partners. First, to align the sample frame as closely as possible with the target population we used, wherever possible, lists of SMEs provided by general business or industry associations to approach firms by e-mail and web sites or, where this was the only alternative, by post. Secondly, to ensure a sufficient number of programme participants to be able to address the issue of interest (i.e. programme effectiveness), we enlisted the support of programme managers to send e-mails to all firms – i.e. both participants and non-participants – who had applied for support in the sample period.

This two-fold strategy succeeded in generating a sample with a reasonable balance between participants (58%) and non-participants (42%) as well as similar characteristics between participants and nonparticipants, except for innovation-related variables and innovation behaviour. Pleasingly, both participants and non-participants in support programmes have similar characteristics with respect to demographics and economic situation: the mean firm age in the sample is 10 years for participants and 9 years for non-participants; while the mean indices of competitive pressure for the two groups are, respectively, 3.72 and 3.89. While participants tend to be somewhat larger than non-participants, micro, small and medium firms

⁸ We found that even trade associations – i.e. organizations that SMEs have chosen to join – find it difficult to obtain information from their own SME members.

are well represented in both groups (respectively, 42% and 58%, 38% and 25%, and 21% and 17%). (Of course, it is the role of matching to control for such differences when programme effects are estimated.) Conversely, as expected, there are differences between participants and non-participants in all categories of innovation and innovation-related variables (see Table 1).

[INSERT TABLE 1 HERE]

Finally, our sample is not only fit for the purpose of identifying programme effects, being reasonably well balanced between participants and non-participants with broadly similar demographic and market characteristics, but is also capable of yielding results of interest from a policy perspective. Given the sampling procedure outlined above, we are unable to assess the extent to which our sample is representative of European SMEs. We also recognise that the use of our findings to inform policy depends on their external validity. Yet, although we do not claim that our SME sample is representative of all European SMEs, we do claim that our sample is useful for informing policy. Indeed, even if a representative sample would have been feasible, we argue that it would not have been useful from a policy perspective. This issue has been recently confronted by Radicic et al. (2015, p.21) in an evaluation arising from a companion Framework 7 project employing the same approach to sampling:

Edith Penrose's classic *The Theory of the Growth of the Firm* (1959, p. 7), addressed a similar issue: "Many firms do not grow, and for a variety of reasons ... I am not concerned with such firms, for I am only concerned with ... those firms that do grow." By analogy, policy makers are concerned to encourage innovative or potentially innovative SMEs to more fully exploit their innovative potential.

In this study, our sample firms are mainly recent innovators (only 27% of participants and 41% of non-participants are in the lowest category of zero to 10% of innovative sales – i.e. the percentage of total sales coming from new products or processes). As long as such firms are a priority for policy makers, then it is valid to use our results to inform policy.

3.3. Model specification

To estimate the individual and joint effects of national and EU R&D programmes, we create treatment variables with the following values:

- treatment=0 if a firm did not participate in national and EU R&D programmes from 2005-2010 (281 firms);
- treatment=1 if a firm participated only in national R&D programmes from 2005-2010 (205 firms);
- treatment=2 if a firm participated only in EU R&D programmes from 2005-2010 (50 firms);
- treatment=3 if a firm participated in both national and EU R&D programmes from 2005-2010 (135 firms).

Our measures of public support are dummy variables, rather than the values of the support. The overwhelming majority of published studies evaluating the effects of public support suffer from the same limitation; in the case of the large literature on R&D subsidy, this is documented by Dimos and Pugh (2016, pp.800 and 811) who also find that ‘using a binary indicator of subsidy – the typical practice in this literature – does not bias estimates in an upward direction’. The reasons for this practice apply with even greater force to studies of SMEs (Radacic et al. 2015). Moreover, the dummy variable approach has the advantage in cross-country studies that it ‘helps avoid potential exchange rate and price-level problems across firms from different countries’ (Lee 2011, p.262).

Two outcome variables are considered in assessing input additionality: a categorical variable *R&D expenditure* (as the share of total expenditure); and a categorical variable *R&D employment* (as the share of the number of employees). Output additionality is evaluated using two innovation output indicators: the variable *Patents* captures patent applications as a binary variable equal to 1 if the firm applied for patents either in the EU or in the US, and zero otherwise; and the categorical variable *Innovative sales* represents the share of sales coming from new products or processes.⁹ Innovative sales is the most frequently used measure of innovation output (Love et al. 2014). Innovative sales is a direct innovation output, while patents measure an intermediate innovation output (Clarysse et al. 2009; Pakes and Griliches 1980). Both patents and innovative sales vary with firm size. Moreover, innovative sales may depend not only on innovation performance but also on market and competition conditions. Accordingly, our empirical models address these issues by controlling for firm size, industry

⁹ Three of these variables – R&D expenditures, R&D employment and patent applications – are used in Czarnitzki and Delonte (2015), while innovative sales is utilized in, for example, Aschhoff and Sofka (2009) and Czarnitzki and Lopes-Bento (2014).

heterogeneity and competitive pressure at firm level. Other measures of innovation output are the introduction of innovation (for example, whether the firm engages in product and/or process innovation) and the number of innovations (Acs and Audretsch 1988). However, the dataset at hand does not contain information on the introduction of innovations.

Each of the Step 1 (treatment) and Step 2 (innovation) models in our three-step approach to estimating programme effects (see Section 3.1) includes the following control variables. Firms' absorptive capacity, as a key driver of successful innovation (Aschhoff and Sofka 2009; Cohen and Levinthal 1990), is measured by three variables. First, a binary variable *R&D department* is introduced to take into account firms' continuous R&D activities (Aschhoff and Sofka 2009). It takes a value of 1 if the firm has a separate R&D department, and zero otherwise. The presence of R&D departments has a positive relation with the likelihood of receiving a subsidy (Antonelli and Crespi 2013; Hussinger 2008). Second, the model specification includes two variables designed to capture firm-level quasi fixed effects (or initial conditions), which should control for time-invariant or slowly-moving unobserved characteristics with respect to innovation (Blundell et al. 1995; for recent applications see (Radicic et al. 2015); Czarnitzki and Delanote 2015; Hagedoorn and Wang 2012): *Resources* measures the resources invested in innovation in 2005 relative to 2009 (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'); while *Innovation capacity* measures the firms' perceived innovation capacities within the industry in 2005 (DV = 1 for 'Above average' and 'Leading'; = 0 for 'Average' and 'Lagging') (see Appendix A.1 for variable definitions).

Other firm characteristics are captured by the following variables. *Export* is a dummy variable equal to one if the firm is engaged in exporting activities, and zero otherwise (Aerts and Schmidt 2008; Alecke et al. 2012; Antonelli and Crespi 2013; Arvanitis et al. 2010; Czarnitzki and Delonte 2015). Because the data are anonymized, we are not able to merge the MAPEER survey with other available datasets containing information about firms' performance, such as productivity, profitability and rates of growth. Nonetheless, a recent strand of the international trade literature linking firm heterogeneity with respect to productivity and participation in foreign markets suggests that by controlling for firms' exporting activities we are, in effect, controlling for productivity (Melitz 2003). As Greenaway and Kneller (2007) explain, high-productivity firms self-select into export markets compared to less productive firms, which resort to the domestic market. However, following Eßig and Glas (2016), we additionally control for firms' turnover by specifying two binary variables: *Turnover10mil* is equal to 1 if the firm reported a turnover above 2 million Euros but less than

10 million Euros (and zero otherwise); and *Turnovermorethan10mil* is equal to 1 if the firm reported a turnover above 10 million Euros (and zero otherwise; the base category is turnover less than 2 million Euros).

Firm size is taken into account by two dummy variables: *Small firms*, equal to one if the firm has more than 10 and less than 50 employees; and *Medium firms*, equal to one if the firm has more than 50 and less than 250 employees (Aerts and Schmidt 2008; Antonelli and Crespi 2013; Arvanitis et al. 2010; Aschhoff and Sofka 2009; Czarnitzki and Delonte 2015). *Age* measuring firm age (in natural logarithms) is included in the model as older firms might be less innovative and thus more reluctant to apply for R&D programmes than their younger counterparts (Alecke et al. 2012; Aschhoff and Sofka 2009; Czarnitzki and Delonte 2015). In contrast, younger firms might be more likely to apply for public support, because the problem of limited financial resources is more pronounced among these firms (Hottenrott and Lopes-Bento 2014). Competitive intensity (*Competition*) is measured as a binary indicator equal to one if the firm reports that the competition is strong in its main markets, and zero otherwise. Sectoral heterogeneity is taken into account by creating six industry categories using the OECD (2006b) taxonomy: high tech; medium high tech; medium low tech; low tech; Information and Communication Technology (ICT); and service sectors (as the base category). Finally, the models include binary indicators for three country groups: Innovation leaders; Moderate innovators; and Modest innovators (Innovation followers is the base category), as noted in Section 3.2.

Finally, models that evaluate output additionality include *R&D expenditures* as an additional matching variable. Czarnitzki and Lopes-Bento (2014) note that the inclusion of the innovation input indicator, such as R&D expenditures, enables the matching algorithm to find suitable matches between firms at different treatment levels, but with the same level of investment in R&D expenditures.

Appendix A.1 provides a detailed description of treatment, outcome and control variables. The modal firm has a share of R&D expenditures in total expenditures of between 11 and 20 per cent. Similarly, the average share of R&D personnel in the total number of employees is between 11 and 20 per cent. Around a quarter (24 per cent) of firms applied for patents, either in the EU or in the US. Two thirds of firms are exporters, while, on average, firms experience weak to moderate competitive pressure. The average age of firms in the sample is 10 years. More than a third of firms have a separate R&D department (39 per cent). Almost half of firms invested more resources in innovation in 2010 than five years earlier (43

per cent), whereas 23 per cent of firms had a past innovation capacity self-reported to be leading or above average in their industry.

4. Main empirical results

The correlation matrix showing the Pearson correlation coefficients among the independent variables is presented in Appendix A.2. The correlations are overall low to moderate suggesting that multicollinearity is minimal. Table 2 reports results from one output variable, as an example; namely, from the multinomial logit model of R&D employment, in which the base is treatment at level 0 (no participation in national and EU R&D programmes).¹⁰ Table 2 also reports the treatment (selection) model, which is the same for all outcome variables. The treatment model shows the effects of covariates on the probabilities of different levels of treatment, while the outcome model estimates the impact of covariates on some particular innovation indicator (in Table 2, R&D employment). The coefficients in the models are not of interest in themselves, as the purpose of specifying the model is to facilitate the estimation of treatment effects (Cattaneo et al. 2013).

[INSERT TABLE 2 HERE]

Appendix A.3 shows the common support regions at different levels of treatment. Treatment effects of any matching estimator based on the propensity score are only estimated in the region of common support (see Section 3.1). Thus, it is necessary to check the overlap of the propensity scores at different treatment levels. The overlap plots, reported in Appendix A.3, reveals that the predicted probabilities are not concentrated near 0 or 1, which implies that the overlap assumption is not violated (Cattaneo et al. 2013).

Table 3 shows the absolute and relative ATTs from the IPWRA estimator for all four outcome variables. Absolute effects represent effects of different treatment levels when the base is treatment 0 (no participation in either national or EU programmes), while relative effects compare the effectiveness of different treatment levels, other than level 0 (Flanagan et al. 2011). First, we consider our two innovation inputs. Receiving support from either national or EU sources or both, relative to non-treated firms, has a positive and highly statistically

¹⁰ Results for the other multinomial logit models (with the other outcome variables) are not reported but are available on request.

significant effects on R&D employment (Columns 1, 2 and 3). Therefore, we have sufficient evidence to reject the null hypothesis of crowding-out from both national and EU R&D programmes on R&D employment. In addition, their joint effect is larger than their individual effects suggesting a complementary effect of both sources together. To quantitatively interpret the estimated treatment effects for the continuous outcome variables (*R&D employment*, *R&D expenditure* and *Innovative sales*), we estimated the means of the predicted outcomes for each treatment level for the comparison group and calculated the differences between the percentage changes of the estimated ATTs and of the means of the predicted outcomes for the comparison group. The results are reported in Table 4 (only statistically significant differences in the percentage changes are presented). SMEs that participated in national support programmes have a 22.3 percentage points higher share of R&D employment than non-participating firms (Column 1), while those firms that received EU support have a 41.4 percentage points higher share of R&D employment than non-participating firms (Column 2). A similar percentage point change is found in SMEs that received support from both sources (Column 3); namely, those firms have a 45.4 percentage points higher share of R&D employment than firms that have not been supported from either source. Regarding relative effects, firms that received support from both sources have a 20.2 percentage points higher share of R&D employment than firms that have been supported by national programmes (Column 5).

[INSERT TABLE 3 HERE]

Focusing on the second measure of innovation input (*R&D expenditure*), firms supported from national programmes have a 16.2 percentage points higher share of R&D expenditure relative to firms without any public support (Column 1), while this effect is much higher for EU support (42 percentage points, Column 2) as well as for support from both sources (33.5 percentage points, Column 3). Regarding relative effects, EU support is marginally more effective than national support; firms that received EU support have a 15 percentage points higher share of R&D expenditure compared to firms that received national support (Column 4). In addition, receiving support from both sources relative to national support (Column 5) increases the share of R&D expenditure by 20.7 percentage points.

Therefore, the results for both input measures – *R&D employment* and *R&D expenditure* – reject crowding-out effects from either national or EU R&D programmes considered separately, thus supporting hypotheses H1A and H2A, while suggesting a larger effect from EU than from national programmes (Column 4) as well as from both levels jointly

compared to national support in isolation (Column 5). Nonetheless, hypothesis H3 can be rejected for both R&D employment and R&D expenditure, as the joint impact of both sources (Column 3) is the same as the impact of EU support in isolation (Column 2) (the difference between the percentage changes in the ATTs is not statistically significant at any conventional level).

Next we consider the findings on our two measures of innovation output, patents and innovative sales. Our results are qualitatively the same for both indicators. Receiving EU support reduces the probability of patent application by 11.3 percentage points relative to receiving no support (Column 2, Table 3), thus supporting hypothesis H4B, and by 12.5 percentage points relative to receiving national support only (Column 4, Table 3).¹¹ In contrast, participating in both national and EU support programmes increases the probability of patent application by 28.1 percentage points compared to EU support in isolation (Column 6, Table 3). For innovative sales as an innovation output indicator, two effects are statistically significant. First, receiving EU support reduces innovative sales by 18.3 percentage points compared to those firms with no support (Column 2, Table 4), thus supporting hypothesis H5B, whereas receiving support from both sources relative to EU support (Column 6, Table 4) increases innovative sales by 26.2 percentage points. In other words, adding national support to EU support more than offsets the crowding out effect associated with EU support, whereas adding EU support to national support makes no significant difference (Column 5, Table 4). Finally, hypothesis H6 is rejected, as the joint impact of both sources is not larger than the impacts of national and EU support programmes in isolation (Column 3, Table 3).

[INSERT TABLE 4 HERE]

Our findings on input additionality corroborate the findings from previous evaluations of R&D and innovation policy for SMEs (e.g. Alecke et al. 2012; Czarnitzki and Delanote 2015; Hottenrott and Lopes-Bento 2014). Concerning output additionality, our findings are weaker with respect to the impact of either national or EU R&D programmes *in isolation* on patent applications and the commercial success of innovation, although we find that national support has a strongly positive effect *when added to* EU support. The relative weakness of these output effects is consistent with Czarnitzki and Lopes-Bento (2014) who found no absolute effects of national and EU funding on innovative sales in German firms (although their study is not focused on SMEs). They suggest that a potential explanation for this finding

¹¹ For patents the Table 3 effects are direct percentage point measures. Hence, they do not figure in Table 4.

could be due to the temporal effects of public funding, i.e. it could be that the effects on the commercialization of innovation occur over the long-run. However, although our investigation is limited by cross-sectional data, the underlying survey questions were framed to capture at least some changes taking place over time. Accordingly, respondents were asked (in 2010): ‘What proportion of your current sales comes from new or substantially improved products or processes introduced since 2005?’ Hence, while output effects from recent R&D support might not yet have had sufficient time to be manifested by the time of interview, output effects from support earlier in our period of interest had had sufficient time to come to the notice of senior management. Hence, unlike Czarnitzki and Lopes-Bento (2014) who find no output effects, we are able to detect some economically substantial and statistically significant output effects. Nonetheless, it is likely that we capture output effects less completely than either input effects (R&D employment and expenditure) or intermediate outputs (patents). This potentially weakens comparison between input, intermediate and output effects – which may appear with different lags – but does not necessarily impair comparison between the effects of support from different administrative levels.

Our focus on the differential effects of support from EU and national levels is consistent with Vītola (2015) who notes that most international R&D programmes stipulate that SMEs engage in international R&D cooperation, while programmes at national level have a wider range of policy instruments. For interpreting our results, one of her conclusions is particularly suggestive; namely, that policy measures at national and international levels differ as they ‘target specific phases of development’ (Vītola 2015, p. 109). This again raises the importance of the timing of R&D support effects. It is possible that national support yields direct commercial benefits within the range of our sample, whereas EU support yields indirect behavioural benefits – via enhanced cooperation – manifested only over periods exceeding the reach of our sample. To investigate this possibility would require longitudinal data over considerable periods.

An additional reason why output effects are less prominent in the literature is suggested by Belitz and Lejpras (2016) who found in the German context that those SMEs intensively participating in R&D programmes are not profiting from innovation. One explanation of this finding is that the German government is liberal in providing support to SMEs without a proven track record.

4.1. Robustness check

For a robustness check, we apply 1:4 Nearest Neighbour (NN) matching with the Mahalanobis metric. Nearest Neighbour (NN) matching is the most commonly used matching estimator in the innovation literature (Czarnitzki et al. 2007). The propensity score can be used to construct matched pairs applying three methods (Guo and Fraser 2010): i) nearest neighbour matching on the estimated propensity score; ii) Mahalanobis metric matching including the estimated propensity score; and iii) nearest Mahalanobis metric matching with calipers based on the propensity score. The third method is superior to others with respect to balancing the covariates between a treatment and comparison group (Rosenbaum and Rubin 1985). To be able to compare the results from a robustness check with our main results, we do not apply the third method, because the use of the caliper would reduce the sample on which the treatment effects are estimated. Thus, we opted for the second method.

In addition, we estimated the 1:4 NN estimator, whereby 1:4 refers to the number of control units used in matching (i.e. four control units were used to match each treated unit). Selecting multiple controls entails a bias-variance trade-off; multiple matches increase bias but reduce variance. The literature does not provide guidelines on how to choose an optimal number of matches (Huber et al. 2010). Following Abadie et al. (2004), we used four matches, as ‘it offers the benefit of not relying on too little information without incorporating observations that are not sufficiently similar’ (p. 298).

The results from NN matching (Table 5) are not only qualitatively the same as the main results but also quantitatively similar (with the exception of innovative sales). Unlike the main results where we reported two statistically significant results for innovative sales (Columns 2 and 6, Table 3), these treatment effects are statistically insignificant when NN matching is estimated. However, these discrepancies do not alter our main conclusions regarding the lack of output additionality and the continuing presence of the “European Paradox”: in particular, the crowding out of patents associated with EU support in isolation (Column 2, Table 5) is again more than offset by the addition of national support; while the same effect is indicated for innovative sales (Column 5, Table 5), even though these estimates are not statistically significant at conventional levels. In addition, the main advantage of the IPWRA estimator (its double robustness property) suggests that, when the true propensity score model is unknown (the most common case in practice), but if either the propensity score model or the outcome model are correctly specified, then the estimated treatment effects are unbiased. In contrast, this double robustness is not a feature of NN matching.

[INSERT TABLE 5 HERE]

5. Conclusions and policy implications

Innovation is centre stage in both national and EU policies. Public policy in support of innovation in SMEs is widespread at all administrative levels. This study empirically assesses whether national and international (EU) R&D programmes induce input and output additionality in European SMEs. In this respect, it follows the recent trend of systematic policy evaluation by assessing two categories of additionality while taking into account the interplay between R&D policies at different governance levels. The empirical strategy takes into account the presence of hidden treatment, whereby firms can participate in either national or EU R&D programmes or both. By estimating treatment effects for different administrative levels together with multi-level governance (receipt of programmes at both national and EU levels), we can make inferences about potential complementary effects between R&D programmes conducted at two administrative levels. Table 6 summarises our findings: absolute effects refer to national and EU programmes in isolation, as well as to their joint effects, in each case relative to “no support”; relative effects measure national and EU support effects in relation to each other. Our discussion in the preceding Section indicates that these findings are both plausible and economically substantial (i.e. neither too large to be implausible nor too small to be of no policy interest).

[INSERT TABLE 6 HERE]

National and EU R&D programmes are effective in increasing firms’ innovation inputs both in isolation (Columns 1 and 2) and jointly (Column 3). However, compared to national support in isolation, EU support is more effective in raising R&D expenditure (Column 4), while for both R&D employment and R&D expenditure, national and EU support are more effective jointly than national support in isolation (Column 5). From the perspective of increasing innovation inputs, firms benefit from participating in both national and international programmes compared to those firms that participate only in national ones. However, this contrasts with our findings for innovation outputs. In isolation, national support has no effect (Column 1), EU support leads to crowding out (Column 2), and both together have no effect (Column 3). Yet, for both patents and innovative sales, the addition of national support to EU support eliminates the crowding-out effect of EU support in isolation (Column 6). Together, this evidence suggests that the “European paradox” applies not only to firms generally but also to SMEs in particular; namely, EU support in isolation promotes innovation inputs but not

innovation outputs. The persistence of this effect is highlighted by the attempts of policy makers at national and EU levels to design measures to mitigate the gap since recognising this paradox some twenty years ago.

While our results provide direct information, they provide only indirect evidence on policy instruments. Nonetheless, our evidence is consistent with the view that supply-side support measures of the type provided at EU and national levels are not effective individually in assisting SMEs to realise innovation outputs. In turn, our evidence provides impetus for the growing emphasis on demand-side support measures. Demand-side policy instruments have been mostly neglected in innovation policy (Crespi and Quatraro 2013) but, in recent years, they are regaining the attention of policy makers, researchers and the business community (Borrás and Edquist 2013), particularly with respect to identifying an appropriate vehicle for supporting SME innovation. Our study provides evidence consistent with increased provision of this type of innovation policy in the SME context.¹² Furthermore, with respect to particular innovation policy instruments, Aschoff and Sofka (2009) found that firms with limited resources, such as small firms, could particularly benefit from public procurement in the domain of market success of innovation.

Finally, this study offers new insights into R&D policy effectiveness in European SMEs, but it also has a few limitations. The most important limitation arises from the timing of support effects. First, input, intermediate and output effects are likely to occur over different periods with the corollary that these support effects are not equally represented in the sample which, in turn, may impair our comparisons between these different effects of support programmes. Second, if national support programmes yield direct relatively rapid commercial benefits, while EU support yields indirect behavioural benefits arising over long periods, then our comparisons between the effects of support from different administrative levels may likewise be impaired. In spite of survey questions designed to capture effects over time, these limitations reflect the type of data typically available to researchers, in particular those concerned with SMEs. In general, the lack of longitudinal data prevents empirical studies of medium- and long-term impacts of public interventions (Alecke et al. 2012; Antonelli and Crespi 2013; Clarysse et al. 2009; Grilli and Murtinu 2011). Moreover, the availability of panel

¹² Cornet et al. (2006) evaluated the effectiveness of a Dutch innovation voucher programme for SMEs, finding that 8 out of 10 vouchers were used to introduce innovations which, without public support, would not have been realized. This is a very large treatment effect, especially given that empirical studies, if reporting additionality at all, typically report small programme effects (Radicic et al. 2015). Secondly, the UK's National Endowment for Science, Technology and the Arts (NESTA) had trialled a voucher programme to support SME purchases of creative services with similarly large treatment effects (Bakhshi et al. 2015).

data would enable the application of estimators that take into account simultaneity and unobserved heterogeneity arising from participation in public support measures. A second limitation, from the perspective of systemic policy evaluations, is that our data precludes the investigation of other types of additionality, such as behavioural additionality and cognitive capacity additionality (Falk 2007; Knockaert et al. 2014). Third, our sample is relatively small thus preventing the analysis of additionality effects at the individual country level. Finally, similar to the questionnaire designed for the Community Innovation Survey, we do not have any detailed information about the forms and objectives of the individual national and international R&D programmes in which firms participated. Thus, our conclusions cannot be applied to any specific R&D programme, but are general and should be interpreted conditional on the analysed dataset (see e.g. Herrera and Sánchez-González 2012). Despite these limitations, our study echoes the conclusion in Cunningham et al. (2013a, p. 35): ‘Even with improved evaluations, thinking about systemic effects will have to be done with limited evidence and in conditions of uncertainty – but it should be attempted nevertheless.’

References

- Abadie, A., Drukker, D., Herr, J.L. and Imbens, G.W. (2004) ‘Implementing matching estimators for average treatment effects in Stata’. *Stata Journal*, 4(3): 290 – 311.
- Abadie A. and Imbens, G. (2006) ‘Large sample properties of matching estimators for average treatment effects’. *Econometrica*, 74(1): 235-267.
- Acs, Z.J. and Audretsch, D.B. (1988) ‘Innovation in large and small firms: An empirical Analysis’. *American Economic Review*, 78(4): 678–690.
- Aerts, K. and Schmidt, T. (2008) ‘Two for the price of one? Additionality effects of R&D subsidies: A comparison between Flanders and Germany’. *Research Policy*, 37(5): 806–22.
- Alecke, B., Mitze, T., Reinkowski, J. and Untiedt, G. (2012) ‘Does Firm Size make a Difference? Analysing the Effectiveness of R&D Subsidies in East Germany’. *German Economic Review*, 13(2): 174–95.
- Antonelli, C. and Crespi, F. (2013) ‘The "Matthew effect" in R&D public subsidies: The Italian evidence’. *Technological Forecasting and Social Change*, 80(8): 1523–34.
- Antonioli, D. and Marzucchi, A. (2012) ‘Evaluating the additionality of innovation policy. A review focused on the behavioural dimension’. *World Review of Science, Technology and Sustainable Development*, (2/3/4): 124–48.
- Arnold, E. (2004) ‘Evaluating research and innovation policy: a systems world needs system evaluations’. *Research Evaluation*, 13(1): 3–17.
- Arrow, K.J. (1962) ‘Economic welfare and the allocation of resources for invention’ in *The Rate and Direction of Inventive Activity: Economic and Social Factors*, R.R. Nelson (eds.), pp. 609–25. Princeton University Press for NBER: Princeton.
- Arvanitis, S., Donze, L. and Sydow, N. (2010) ‘Impact of Swiss technology policy on firm

- innovation performance: an evaluation based on a matching approach'. *Science and Public Policy*, 37(1): 63-78.
- Arvanitis, S. (2013) 'Micro-econometric approaches to the evaluation of technology-oriented public programmes: a non-technical review of the state of the art' in *Handbook on the theory and practice of program evaluation*, A.N. Link and N.S. Vonortas (eds), pp. 56–88. Cheltenham: Edward Elgar.
- Aschhoff, B. and Sofka, W. (2009) 'Innovation on demand- Can public procurement drive market success of innovation?' *Research Policy*, 38(8): 1235–47.
- Bakhshi, H., Edwards, J.S., Roper, S., Scully, J., Shaw, D., Morley, L. and Rathbone, N. (2015) 'Assessing an experimental approach to industrial policy evaluation: Applying RCT+ to the case of Creative Credits'. *Research Policy*, 44(8): 1462-72.
- Belitz, H. and Lejpras, A. (2016) 'Financing patterns of R&D in small and medium-sized enterprises and the perception of innovation barriers in Germany'. *Science and Public Policy*, 43(2): 245–61.
- Bleda, M. and del Río, P. (2013) 'The market failure and the systemic failure rationales in technological innovation systems'. *Research Policy*, 42(5): 1039–52.
- Blundell, R., Griffith, R. and Van Reenan, J. (1995) 'Dynamic Count Data Models of Technological Innovation'. *Economic Journal*, 105(429): 333-44.
- Boekholt, P. (2010) 'The evolution of innovation paradigms and their influence on research, technological development and innovation policy instruments' in *The Theory and Practice of In-novation Policy - An International Research Handbook*, R. Smits, S. Kuhlmann and P. Shapira (eds), pp. 333-59. Cheltenham: Edward Elgar.
- Borrás, S. and Edquist, C. (2013) 'The choice of innovation policy instruments'. *Technological Forecasting and Social Change*, 80(8): 1513–22.
- Busso, M., DiNardo, J. and McCrary, J. (2014) 'New evidence on the finite sample properties of propensity score reweighting and matching estimators'. *Review of Economics and Statistics*, 96(5): 885-897.
- Caliendo, M. and Kopeinig, S. (2008) 'Some Practical Guidance for the Implementation of Propensity Score Matching'. *Journal of Economic Surveys*, 22 (1): 31–72.
- Cattaneo, M. D., Drukker, D.M. and Holland, A.D. (2013). 'Estimation of multivalued treatment effects under conditional independence'. *Stata Journal*, 13(3): 407–50.
- Cerulli, G. (2010) 'Modelling and Measuring the Effect of Public Subsidies on Business R&D: A Critical Review of the Econometric Literature'. *Economic Record*, 86(274): 421–49.
- Clarysse, B., Wright, M. and Mustar, P. (2009) 'Behavioural additionality of R&D subsidies: A learning perspective'. *Research Policy*, 38(10): 1517–33.
- Cornet M., Vroomen B., van der Steeg M. (2006) 'Do innovation vouchers help SMEs to cross the bridge towards science?'. CBP Discussion Paper 58, CPB Netherlands Bureau for Economic Policy Analysis.
- Czarnitzki, D., Ebersberger B. and Fier, A. (2007) 'The Relationship between R&D Collaboration, Subsidies and R&D Performance: Empirical Evidence from Finland and Germany'. *Journal of Applied Econometrics*, 22(7): 1347–366.
- Cunningham, P., Edler, J., Flanagan, K. and Laredo, P. (2013a) 'Innovation policy mix and interaction: a review'. NESTA Working Paper 13/20.

- Cunningham, P., Gök, A. and Laredo, P. (2013b) 'The Impact of Direct Support to R&D and Innovation in Firms'. NESTA Working Paper 13/03.
- Czarnitzki, D. and Lopes-Bento, C. (2012) 'Evaluation of public R&D policies: A cross-country comparison'. *World Review of Science Technology and Sustainable Development*, 9(2-4): 254–82.
- Czarnitzki, D. and Lopes-Bento, C. (2014) 'Innovation Subsidies: Does the Funding Source Matter for Innovation intensity and Performance? Empirical evidence from Germany'. *Industry and Innovation*, 21(5): 380–409.
- Czarnitzki, D. and Delanote, J. (2015) 'R&D policies for young SMEs: input and output effects'. *Small Business Economics*, 45: 465–85.
- Dai, X. and Cheng, I. (2015) 'The effect of public subsidies on corporate R&D investment: An application of the generalized propensity score'. *Technological Forecasting and Social Change*, 90: 410–419.
- David, P.A. and Hall, B.H. (2000) 'Heart of Darkness: Modelling Public-Private Funding Interactions inside the R&D Black Box'. *Research Policy*, 29(9): 1165–83.
- David, P.A., Hall, B.H., and Toole, A.A. (2000) 'Is Public R&D a Complement or Substitute for Private R&D? A review of the Econometric Evidence'. *Research Policy*, 29(4–5): 497–529.
- Dimos, C. and Pugh, G. (2016) 'The effectiveness of R&D subsidies: a meta-regression analysis of the evaluation literature'. *Research Policy*, 45(4):797–815.
- Dosi, G., Llerena, P. and Labini, M.S. (2006) 'The relationships between science, technologies and their industrial exploitation: An illustration through the myths and realities of the so-called 'European Paradox''. *Research Policy*, 35(10): 1450–64.
- Edler, J., Berger, M., Dinges, M. and Gök, A. (2012a) 'The practice of evaluation in innovation policy in Europe'. *Research Evaluation*, 21(3):167–82.
- Edler, J. and Georghiou, L. (2007) 'Public procurement and innovation - resurrecting the demand side'. *Research Policy*, 36(7): 949–63.
- Edler, J., Georghiou, L., Blind, K. and Uyerra, E. (2012b) 'Evaluating the demand side: New challenges for evaluation'. *Research Evaluation*, 21(1): 33–47.
- Emsley, R., Lunt, M., Pickles, A. and Dunn, G. (2008) 'Implementing double-robust estimators of causal effects'. *Stata Journal*, 8(3): 334–53.
- Eßig, M. and Glas, A.H. (2016) 'Considering small and medium-sized suppliers in public procurement – the case of the German defence sector' in *Logistics Management, Lecture Notes in Logistics*, D. Mattfeld, T. Spengler, Brinkmann, J. and M. Grunewald (eds), pp. 19-33. Switzerland: Springer International Publishing.
- European Commission (1995) 'The Green Paper on Innovation'. COM (95) 688 final. 20 December 1995.
- European Commission (2005) 'SME definition'.
http://ec.europa.eu/enterprise/policies/sme/facts-figures-analysis/sme-definition/index_en.htm.
- European Commission (2010) 'Europe 2020: A European strategy for smart, sustainable and inclusive growth'.
<http://ec.europa.eu/eu2020/pdf/COMPLET%20EN%20BARROSO%20%20%20007%20-%20Europe%202020%20-%20EN%20version.pdf>.

- European Commission (2011) 'European Innovation Scoreboard'. Brussels.
- European Commission (2013) 'State of the Innovation Union 2012: Accelerating change'. http://ec.europa.eu/research/innovation-union/pdf/state-of-the-union/2012/state_of_the_innovation_union_report_2012.pdf, 2013.
- Falk, R. (2007) 'Measuring the effects of public support schemes on firms' innovation activities: Survey evidence from Austria'. *Research Policy*, 36(5): 665–79.
- Foreman-Peck, J. (2013) 'Effectiveness and Efficiency of SME Innovation Policy'. *Small Business Economics*, 41(1): 55–70.
- Flanagan, K., Uyarra, E. and Laranja, M. (2011) 'Reconceptualising the "policy mix" for innovation'. *Research Policy*, 40(5): 702–13.
- García-Quevedo, J. (2004) 'Do Public Subsidies Complement Business R&D? A Meta-Analysis of the Econometric Evidence'. *Kyklos*, 57(1): 87–107.
- Gök, A. and Edler, J. (2012) 'The use of behavioural additionality evaluation in innovation policy making'. *Research Evaluation*, 21(4): 306–19.
- González, X., Jaumandreu, J. and Pazó, C. (2005) 'Barriers to innovation and subsidy effectiveness'. *RAND Journal of Economics*, 36(4): 930–50.
- González, X. and Pazó, C. (2008) 'Do public subsidies stimulate private R&D spending?'. *Research Policy*, 37(3): 371–89.
- Greenaway, D. and Kneller, R. (2007) 'Firm heterogeneity, exporting, and foreign direct investment'. *Economic Journal*, 117(517): 134–161.
- Grilli, L. and Murtinu, S. (2011) 'Econometric evaluation of public policies for science and innovation: a brief guide to practice' in *Science and Innovation Policy for the New Knowledge Economy (PRIME Series on Research and Innovation Policy in Europe)*, M.G. Colombo, L. Grilli, L. Piscitello, and C. Rossi –Lamastra (eds), pp. 60–75. Edward Elgar Publishing Ltd.
- Guerzoni, M. and Raiteri, E. (2015) 'Demand-side vs. supply-side technology policies: Hidden treatment and new empirical evidence on the policy mix'. *Research Policy*, 44(3): 726–47.
- Guo, S. and Fraser, M.W. (2010) *Propensity Score Analysis: Statistical Methods and Applications*. (1st edition). Sage Publications, Inc.
- Hagedoorn, J. and Wang, N. (2012) 'Is there complementarity or substitutability between internal and external R&D strategies?'. *Research Policy* 41(6): 1072–83.
- Hammadou, H., Paty, S. and Savona, M. (2014) 'Strategic interactions in public R&D across European countries: A spatial econometric analysis'. *Research Policy*, 43(7): 1217–26.
- Heckman, J.J. and Vyttilacil, E.J. (2007) 'Econometric evaluation of social programs, part I: causal models, structural models and econometric policy evaluation' in *Handbook of Econometrics*, J.J. Heckman and E.E. Leamer (eds), vol. 6, no. 6b, pp. 4779–873. Elsevier.
- Herrera, L. and Sánchez-González, G. (2012) 'Firm size and innovation policy'. *International Small Business Journal*, 31(2): 137–55.
- Hewitt-Dundas, N. and Roper, S. (2010) 'Output Additionality of Public Support for Innovation: Evidence for Irish Manufacturing Plants'. *European Planning Studies*, 18(1): 107–22.

- Hirano, K., Imbens, G.W. and Ridder, G. (2003) 'Efficient estimation of average treatment effects using the estimated propensity score'. *Econometrica*, 71(4): 1161–89.
- Hottenrott, H. and Lopes-Bento, C. (2014) '(International) R&D collaboration and SMEs: The effectiveness of targeted public R&D support schemes'. *Research Policy*, 43(6): 1055–66.
- Huber, D., Lechner, M. and Wunch, C. (2010) 'How to Control for Many Covariates? Reliable Estimators Based in the Propensity Score'. *IZA Discussion Paper*, No. 5268.
- Hussinger, K. (2008) 'R&D and subsidies at the firm-level: An application of parametric and semiparametric two-step selection models'. *Journal of Applied Economics*, 23(6): 729–47.
- Imbens, G.W. (2004) 'Nonparametric Estimation of Average Treatment Effects under Exogeneity: A Review'. *Review of Economics and Statistics*, 86(1): 4–29.
- Imbens, G.W. and Wooldridge, J.M. (2009) 'Recent Developments in the Econometrics of Program Evaluation'. *Journal of Economic Literature*, 47(1): 5–86.
- Kline, S.J. and Rosenberg, N. (1986) 'An overview of innovation' in *The Positive Sum Strategy: Harnessing Technology for Economic Growth*, R. Landau and N. Rosenberg (eds), pp. 275–305. Washington, D.C.: National Academy Press.
- Knockaert, M., Spithoven, A. and Clarysse, B. (2014) 'The impact of technology intermediaries on firm cognitive capacity additionality'. *Technological Forecasting and Social Change*, 81(1): 376–87.
- Lee, H.-Y. (2011) 'The differential effects of public R&D support on firm R&D: Theory and evidence from multi-country data'. *Technovation*, 31(5-6), 256-69.
- Love, J.H., Roper S. and Vahter, P. (2014) 'Learning from openness: The dynamics of breadth in external innovation linkages'. *Strategic Management Journal* 35(11): 1703–1716.
- Magro, E. and Wilson, J.R. (2013) 'Complex innovation policy systems: Towards an evaluation mix'. *Research Policy*, 42(9): 1647–56.
- Marino, M., Lhuillery, S., Parrotta, P. and Sala, D. (2016) 'Additionality or crowding-out? An overall evaluation of public R&D subsidy in private R&D expenditure'. *Research Policy*, [DOI:10.1016/j.respol.2016.04.009](https://doi.org/10.1016/j.respol.2016.04.009).
- Martin, B.R. (2016) 'R&D policy instruments – a critical review of what we do and don't know'. *Industry and Innovation*, [DOI:10.1080/13662716.2016.1146125](https://doi.org/10.1080/13662716.2016.1146125).
- Melitz, M. (2003) 'The impact of trade on intra-industry reallocations and aggregate industry Productivity'. *Econometrica*, 71(6): 1695–1725.
- Nelson, R.R. (1959) 'The simple economics of basic research'. *Journal of Political Economy*, 67(3): 97–306.
- Nemet, G.F. (2009) 'Demand-pull, technology-push, and government-led incentives for non-incremental technical change'. *Research Policy*, 38(5): 700–9.
- OECD (1998) *New rationale and approaches in technology and innovation policy*. STI Review 22. Paris Publishing, Paris: Organisation for Economic Co-Operation and Development.
- OECD (2006a) *Government R&D Funding and Company Behaviour: Measuring Behavioural Additionality*. Paris Publishing, Paris: Organisation for Economic Co-Operation and Development.

- OECD (2006b) *Science, Technology and Industry Outlook*. Paris Publishing, Paris: Organisation for Economic Co-Operation and Development.
- OECD (2010) 'The Innovation Policy Mix' in *OECD Science, Technology and Industry Outlook 2010*, OECD Publishing.
- OECD (2012) *Science, Technology and Industry Outlook 2012*. Paris Publishing, Paris: Organisation for Economic Co-Operation and Development.
- Pakes, A. and Griliches, Z. (1980) 'Patents and R&D at the firm level: A first report'. *Economics Letters*, 5(4): 377–381.
- Penrose, E.T. (1959) *The Theory of the Growth of the Firm*. Oxford: Oxford University Press.
- Piper, A.T. (2015) 'Sliding down the U-shape? A dynamic panel investigation of the age-well-being relationship, focusing on young adults'. *Social Science & Medicine*, 143: 54-61.
- Podsakoff, P.M. and Organ, D.W. (1986) 'Self-reports in organizational research: Problems and prospects'. *Journal of Management*, 12(4): 69–82.
- Radicic, D., Pugh, G., Hollanders, H., Wintjes, R. and Fairburn, J. (2015) 'The impact of innovation support programmes on SME innovation in traditional manufacturing industries: an evaluation for seven EU regions'. *Environment and Planning C: Government and Policy*. DOI: 10.1177/0263774X15621759.
- Rosenbaum, P.R. and Rubin, D.B. (1985) 'Constructing a Control Group Using Multivariate Matched Sampling Methods That Incorporate the Propensity Score'. *American Statistician*, 39(1): 33–38.
- Scherngell, T. and Barber, M.J. (2011) 'Distinct spatial characteristics of industrial and public research collaborations: evidence from the fifth EU Framework Programme'. *Annals of Regional Science*, 46(2): 247–66.
- Smith, K. (2000) 'Innovation as a systemic phenomenon: rethinking the role of policy'. *Enterprise & Innovation Management Studies*, 1(1): 73–102.
- Steiner, P.M., Cook, T.D., Shadish, W.R. and Clark, M.H. (2010) 'The Importance of Covariate Selection in Controlling for Selection Bias in Observational Studies'. *Psychological Methods*, 15(3): 250–67.
- Vītola, A. (2015) 'Innovation policy mix in a multi-level context: The case of the Baltic Sea Region countries'. *Science and Public Policy*, 42(3):401–14.
- Wooldridge, J.M. (2010) *Econometric Analysis of Cross Section and Panel Data*. (2nd edition). MIT Press.
- Zúñiga-Vicente, J., Alonso-Borrego, C., Forcadell, F.J. and Galán, J.I. (2014) 'Assessing the effect of public subsidies on firm R&D investment: a survey'. *Journal of Economic Surveys*, 28(1): 36–67.

[INSERT APPENDIX A.1 HERE]

[INSERT APPENDIX A.2 HERE]

[INSERT APPENDIX A.3 HERE]

Table 1. Mean values of the independent variables for participating and non-participating firms.

Independent variables	Participants	Non-participants
R&D personnel	2.460	1.571
R&D expenditure	2.343	1.530
Patents	0.304	0.139
Innovative sales	3.698	3.077
Export	0.742	0.526
Turnover10million	0.251	0.188
Turnovermorethan10mill	0.084	0.059
Age	2.322	2.208
Competition	3.716	3.892
Innovation capacity	0.279	0.164
Resources	0.488	0.348
R&D department	0.522	0.213
Micro firms	0.419	0.582
Small firms	0.376	0.247
Medium firms	0.205	0.171

Table 2. Estimation functions (the outcome and the treatment models) for the outcome variable R&D employment with treatment level 0 as the base (reference) category.

Independent variables	Outcome models				Treatment model		
	Potential -outcome model for treatment =0	Potential -outcome model for treatment =1	Potential -outcome model for treatment =2	Potential -outcome model for treatment =3	<i>Treatment</i> =1	<i>Treatment</i> =2	<i>Treatment</i> =3
Export	0.266* (0.154)	0.218 (0.164)	0.188 (0.238)	-0.260 (0.207)	0.418* (0.222)	1.107*** (0.407)	1.094*** (0.306)
Age	-0.233** (0.096)	-0.288*** (0.092)	0.008 (0.166)	-0.052 (0.137)	0.007 (0.125)	0.151 (0.196)	0.254* (0.142)
Turnover between two and ten million	0.088 (0.237)	-0.112 (0.218)	-0.785* (0.421)	-0.764*** (0.287)	0.253 (0.341)	0.846* (0.483)	-0.059 (0.365)
Turnover more than ten million	0.097 (0.269)	-0.517* (0.272)	-2.271*** (0.779)	-1.112** (0.436)	0.625 (0.551)	0.542 (0.798)	0.103 (0.610)
Competition	-0.065 (0.064)	-0.051 (0.075)	-0.328*** (0.090)	0.039 (0.116)	-0.357*** (0.108)	-0.130 (0.164)	-0.255** (0.124)
Innovation capacity	0.341* (0.179)	0.675*** (0.168)	0.141 (0.248)	0.264 (0.207)	0.273 (0.273)	1.164*** (0.368)	1.063*** (0.294)
Resources	0.146 (0.123)	-0.111 (0.142)	-0.335 (0.267)	0.067 (0.193)	0.765*** (0.219)	0.395 (0.335)	1.000*** (0.253)
R&D department	0.562*** (0.161)	0.575*** (0.152)	-0.116 (0.195)	0.866*** (0.194)	1.194*** (0.228)	0.257 (0.391)	0.949*** (0.259)
Small firms	-0.589*** (0.181)	-0.591*** (0.198)	0.630*** (0.218)	-0.265 (0.221)	0.397 (0.267)	-0.136 (0.461)	0.886*** (0.317)
Medium firms	-0.512** (0.255)	-0.472 (0.318)	-0.079 (0.383)	-0.243 (0.332)	-0.310 (0.426)	-0.492 (0.665)	0.431 (0.499)
Industry dummies	Included	Included	Included	Included	Included	Included	Included
Country group dummies	Included	Included	Included	Included	Included	Included	Included
Constant	2.018*** (0.517)	2.943*** (0.386)	4.065*** (0.873)	2.501*** (0.780)	-0.630 (0.617)	-3.881*** (1.009)	-4.486*** (0.889)
No of observations	671						

Notes: Robust standard errors in parentheses; *** p<0.01, ** p<0.05, * p<0.1.

Table 3. Estimated Average Treatment Effects on the Treated (ATTs) using the IPWRA estimator.

Outcome variables	Absolute treatment effects			Relative treatment effects		
	National support versus no support	EU support versus no support	Both sources versus no support	EU support versus national support	Both sources versus national support	Both sources versus EU support
	1.	2.	3.	4.	5.	6.
R&D employment	0.414*** (0.100)	0.755*** (0.163)	0.842*** (0.110)	0.184 (0.195)	0.471*** (0.117)	0.021 (0.143)
R&D expenditure	0.300*** (0.100)	0.740*** (0.165)	0.645*** (0.109)	0.326* (0.185)	0.440*** (0.107)	-0.065 (0.131)
Patents	0.032 (0.049)	-0.113* (0.060)	0.036 (0.078)	-0.125** (0.061)	0.041 (0.058)	0.281*** (0.061)
Innovative sales	-0.210 (0.204)	-0.756** (0.367)	-0.306 (0.277)	-0.542 (0.361)	-0.024 (0.243)	0.801*** (0.303)

Notes: Robust standard errors in parentheses; *** p<0.01, ** p<0.05, * p<0.1.

Table 4. Percentage changes relative to the base-level predicted outcomes.

Outcome variables	Absolute treatment effects			Relative treatment effects		
	National support versus no support	EU support versus no support	Both sources versus no support	EU support versus national support	Both sources versus national support	Both sources versus EU support
	1.	2.	3.	4.	5.	6.
R&D employment	0.223*** (0.060)	0.414*** (0.099)	0.454*** (0.073)	-	0.202*** (0.071)	-
R&D expenditure	0.162*** (0.060)	0.420*** (0.104)	0.335*** (0.068)	0.150* (0.089)	0.207*** (0.056)	-
Innovative sales	-	-0.183** (0.082)	-	-	-	0.262** (0.118)

Notes: Standard errors in parentheses; *** p<0.01, ** p<0.05, * p<0.1.

Table 5. Estimated Average Treatment Effects on the Treated (ATTs) using 1:4 Nearest Neighbour (NN) matching.

Outcome variables	Absolute treatment effects			Relative treatment effects		
	National support versus no support	EU support versus no support	Both sources versus no support	EU support versus national support	Both sources versus national support	Both sources versus EU support
	1.	2.	3.	4.	5.	6.
R&D employment	0.488*** (0.142)	0.885*** (0.204)	0.893*** (0.158)	0.205 (0.217)	0.311** (0.145)	-0.109 (0.215)
R&D expenditure	0.378*** (0.134)	0.910*** (0.204)	0.737*** (0.131)	0.180 (0.215)	0.231* (0.135)	0.007 (0.215)
Patents	0.067 (0.048)	-0.095* (0.057)	0.063 (0.106)	-0.135* (0.075)	0.050 (0.064)	0.200** (0.083)
Innovative sales	-0.112 (0.245)	-0.330 (0.361)	0.276 (0.418)	-0.465 (0.389)	-0.139 (0.288)	0.485 (0.398)

Notes: Abadie-Imbens (2006) standard errors in parentheses; *** p<0.01, ** p<0.05, * p<0.1.

Table 6. Summary of findings.

Outcome variables	Absolute effects: national and EU programmes in isolation and jointly			Relative effects: national and EU effects in relation to each other		
	National support versus no support	EU support versus no support	Both sources versus no support	EU support versus national support	Both sources versus national support	Both sources versus EU support
	1.	2.	3.	4.	5.	6.
R&D employment	Crowding out rejected	Crowding out rejected	Crowding out rejected	No difference	Higher effect from both sources jointly than from national support in isolation	No difference
R&D expenditure	Crowding out rejected	Crowding out rejected	Crowding out rejected	Higher effect of EU than national support ^a	Higher effect from both sources jointly than from national support in isolation	No difference
Patents	No effect	Crowding out not rejected ^a	No effect	Lower effect of EU than national support ^a	No difference	Higher effect: crowding out from EU support eliminated by combination with national support
Innovative sales	No effect	Crowding out not rejected	No effect	Lower effect of EU than national support ^a	No difference	Higher effect: crowding out from EU support eliminated by combination with national support

Note: ^a At the 10% level.

Appendix A1. Variable definition and descriptive statistics (mean and standard deviation).

Variables	Variable construction	Mean	Standard deviation
Treatment variable			
Treatment	=0 if a firm did not participate in national and international R&D programmes =1 if a firm only participated in national R&D programmes =2 if a firm only participated in international R&D programmes =3 if a firm participated in both national and international R&D programmes	1.058	1.139
Outcome variables			
R&D expenditure (share of R&D expenditure in total expenditures)	Categorical variable =1 if the share is 0-10 %; =2 if the share is 11-20%; =3 if the share is 21-50 %; =4 if the share is >50%	2.003	1.116
R&D employment (share of R&D personnel in total number of employees)	Categorical variable =1 if the share is 0-10 %; =2 if the share is 11-20%; =3 if the share is 21-50 %; =4 if the share is >50%	2.088	1.201
Patents	DV=1 if a firm applied for either EU or US patents; zero otherwise	0.237	0.426
Innovative sales - share of sales from new products and processes	Categorical variable =1 if the share is 0-10 %; =2 if the share is 11-20%; =3 if the share is 21-30 %; =4 if the share is 31-40%; =5 if the share is 41-50%; =6 if the share is >50%	3.456	2.146
Control variables			
Degree of internationalization (<i>Export</i>)	DV=1 if a firm engages in exporting activities; zero otherwise	0.653	0.476
The age of firm (<i>Age</i>)	Natural logarithm of firm age in the reference year (the reference year is either 2008, 2009 or 2010)	2.274	0.971
Firm's turnover (<i>Turnover less than two million</i>) (base category)	DV=1 if a firm reported turnover that is less than 2 million Euros in the reference year; zero otherwise	0.699	0.459
Firm's turnover (<i>Turnover between two and ten million</i>)	DV=1 if a firm reported turnover that is larger than 2 million and smaller than 10 million Euros in the reference year; zero otherwise	0.227	0.419
Firm's turnover (<i>Turnover more than ten million</i>)	DV=1 if a firm reported turnover that is larger than 10 million Euros in the reference year; zero otherwise	0.074	0.263
Competitive pressure (<i>Competition</i>)	Categorical variable =1 if the response was 'Very weak'; =2 if the response was 'Weak'; =3 if the response was 'Moderate'; =4 if the response was 'Strong'; =5 if a firm responded 'Very strong' to the question "How would you judge the competition in your main market(s)"	3.791	1.018
Existence of a separate R&D department (<i>R&D department</i>)	DV=1 if a firm has a separate R&D department; zero otherwise	0.393	0.489
Resources devoted to innovation (<i>Resources</i>)	DV=1 if a firm's response to the question "Five years ago did you devote?" was 'Fewer resources to innovation'; = 0 if 'About the same' or 'More'.	0.426	0.495

Past innovation capacity relative to competitors (<i>Innovation capacity</i>)	DV = 1 if a firm's innovation capacities within the industry in 2005 was 'Above average' and 'Leading'; = 0 for 'Average' and 'Lagging'	0.231	0.422
Micro firms	DV=1 if a firm has fewer than 10 employees; zero otherwise	0.483	0.500
Small firms	DV=1 if a firm has more than 10 and fewer than 50 employees; zero otherwise	0.325	0.469
Medium firms	DV=1 if a firm has more than 50 and fewer than 250 employees; zero otherwise	0.192	0.394
'Innovation leaders', that is, countries whose performance is well above the EU27 average (<i>Leaders</i>)	DV=1 if countries are Denmark, Finland, Germany and Sweden; zero otherwise	0.171	0.377
'Innovation followers', that is, countries whose performance is close to that of the EU27 average (<i>Followers</i>) (base category)	DV=1 if countries are Austria, Belgium, Cyprus, Estonia, France, Ireland, Luxembourg, Netherlands, Slovenia and the United Kingdom; zero otherwise	0.282	0.450
'Moderate innovators', that is, countries whose performance is below that of the EU27 average (<i>Moderate</i>)	DV=1 if countries are Czech Republic, Greece, Hungary, Italy, Malta, Poland, Portugal, Slovakia and Spain; zero otherwise	0.387	0.488
'Modest innovators', that is, countries whose performance is well below that of the EU27 average (<i>Modest</i>)	DV=1 if countries are Bulgaria, Latvia, Lithuania, Romania and Bosnia and Herzegovina; zero otherwise	0.159	0.366
High-technology industries	DV=1 if a firm operates in high-technology intensive industries; zero otherwise (NACE classification rev 1.1)	0.183	0.387
Medium high-technology industries	DV=1 if a firm operates in medium high-technology intensive industries; zero otherwise	0.130	0.336
Medium low-technology industries	DV=1 if a firm operates in medium low-technology intensive industries; zero otherwise	0.133	0.339
Low-technology industries	DV=1 if a firm operates in low-technology intensive industries; zero otherwise	0.155	0.362
Information and Communication Technology (ICT) industries	DV=1 if a firm operates in ICT industries; zero otherwise	0.203	0.402
Service sectors	DV=1 if a firm operates in service industries; zero otherwise (base category)	0.197	0.398

Appendix A2. The correlation matrix.

	1.	2.	3.	4.	5.	6.	7.	8.	9.
1. Export	1.000								
2. Age	0.063	1.000							
3. Turnover between two and ten	0.073*	0.273***	1.000						
4. Turnover more than ten	0.088**	0.269***	-0.154***	1.000					
5. Competition	0.026	0.115***	0.118***	0.014	1.000				
6. Innovation capacity	0.132***	-0.082**	-0.052	-0.034	-0.107***	1.000			
7. Resources	0.021	-0.021	0.023	-0.015	0.112***	-0.086**	1.000		
8. R&D department	0.222***	0.072*	0.118***	0.155***	0.003	0.116***	0.114***	1.000	
9. R&D expenditure	0.193***	-0.245***	-0.142***	-0.128***	-0.148***	0.063	0.281***	0.359***	1.000

Appendix A3. Checking the overlap assumption (the common support region).

