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Rita Nana-Cheraa
The Productivity Institute
Enterprise Research Centre
Warwick Business School
Rita.Nana-Cheraa.1@wbs.ac.uk

Stephen Roper
The Productivity Institute,
Enterprise Research Centre, Innovation and Research Caucus,
and National Innovation Centre for Rural Enterprise,
Warwick Business School
Stephen.roper@wbs.ac.uk

Kevin Mole
Enterprise Research Centre,
and National Innovation Centre for Rural Enterprise,
Warwick Business School
Kevin.Mole@wbs.ac.uk

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ABSTRACT

This study provides empirical evidence on the input and output additionality achieved by UK firms receiving R&D tax incentives only, R&D and innovation grants only, and a combination of both incentives. Four key findings emerge. First, we find strong evidence of input additionality from each type of public support but also some attenuation or substitution effects between the input additionality of grants and tax-incentives. Second, innovation output additionality is consistently positive from tax-incentive-only, and the related policy-mix. However, grant-only output additionality effects are notably smaller in scale and statistically much weaker. Here, we also observe complementarity between tax and grant measures leading to stronger policy-mix output additionality. Third, we find a, perhaps surprising, difference in the scale of input and output additionality effects for tax incentives-only and the related policy mix: input additionality effects are consistently larger – 2-3 times – the scale of output additionality effects. Fourth, the relationship between input and output additionality varies between groups of firms. In terms of productivity, input (output) additionality is stronger (weaker) among low productivity firms, while input (output) additionality is weaker (stronger) in high productivity enterprises. Our results suggest that: (a) policy evaluation or targeting based on input additionality alone may significantly over-estimate or mis-represent long-term policy benefits; and (b) that 'average' estimates for additionality effects may provide a misleading indication of additionality profiles for different types of firms.

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Keywords: R&D; innovation; policy mix; grant; tax incentives

JEL Codes: O38, O31, O30

CONTENTS

1. INTRODUCTION

Across the globe governments provide support to private sector R&D and innovation through a range of policy schemes including direct R&D subsidies and indirect R&D tax incentives. As a result, firms receiving support often benefit from a blend of policies to support their R&D and innovation activities leading to potential interactions between the various support instruments. The effects of such interactions could be either synergistic (Haegeland and Møen 2007; Guerzoni and Raiteri 2015), neutral, or even lead to a reduction in the potential effect of the individual policies (Marino et al. 2016). Despite the potential significance of these effects, relatively little research has been undertaken on the impact of policy mix - when firms receive a combination of incentives - and how it relates to business outcomes. Haegeland and Møen (2007) and Marino et al. (2016) are among the few that have examined policy mix effects on firm performance providing conflicting evidence. Haegeland and Møen (2007) studied Norwegian firms and found a complementary effect when R&D subsidies interacted with the R&D tax credit. However, Marino et al. (2016) found evidence to suggest that mixing French tax credits with R&D subsidies reduces the additionality of public support.

These contradictory findings suggest the importance of using comprehensive datasets which enable policy mix evaluations, since evaluating individual policy effects without accounting for other related supports may lead to a hidden treatment bias. That is, evaluating individual policies in isolation might lead to over- or under-estimation of the individual policy impact (Guerzoni and Raiteri 2015; Busom et al. 2015). The focus of our analysis here is therefore to further examine policy mix effects on R&D spending, i.e., input additionality, and innovation outcomes, i.e., output additionality, among the same group of UK firms. In terms of input additionality, analysis of the separate effects of R&D subsidies and R&D tax incentives on innovation inputs (e.g., R&D investment, R&D employment) has received extensive attention in the literature (García-Quevedo, 2004). This evidence suggests that the separate policies can generate significant input additionality, however, our understanding of policy mix effects on input additionality remains limited. In terms of output additionality, the individual effect of R&D subsidies and R&D tax incentives on innovation outputs (e.g., patenting, product, and process innovation) has received some attention in the literature, although this is not as extensive as the consideration given to input additionality effects (García-Quevedo, 2004)[1]. Relatively few studies have, however,

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[1] Although the overall finding by the literature is ambiguous, most studies conclude there is complementarity between public and private funding (see e.g., Sterlacchini and Venturini 2019;

considered the link between policy mix and innovation outcomes. Lenihan and Mulligan (2018) attribute this gap in the literature to the lack of firm-level datasets which capture the variety of innovation measures beyond R&D expenditure as well as detailed information on the types of innovation support which businesses receive (Guerzoni and Raiteri 2015; Radicic and Pugh 2017). Here, building on UK data which does allow this type of policy mix analysis we aim to establish: (a) whether individual support measures for R&D and innovation do generate input and output additionality; and (b) whether interactions between policy instruments create either a synergistic-, neutral- or substitution-effect on input and output additionality (Flanagan et al. 2011). A major concern in this type of analysis are issues of selectivity and endogeneity. Since subsidy recipients are not randomly selected, supported and non-supported firms may differ substantially. In this situation, if the receipt of public support is related to some covariates that are correlated with performance but are not accounted for in the analysis, then any potential policy effect being estimated in the evaluation may not necessarily reflect the true causal relationship between policy support and performance. To account for this issue, the current study uses coarsened exact matching and the propensity score matching techniques, normally used in the program evaluation literature (e.g., Heckman et al. 1997; Guerzoni and Raiteri 2015; Hünermund and Czarnitzki 2019), to identify a valid control group for firms receiving support (i.e., treated). The propensity score matching process allows us to control for any confounding influence of pre-treatment control variables in our dataset to estimate causal treatment effects.

We make four main contributions to the literature on firm-level innovation and public policy. First, we empirically operationalise the policy mix concept, and document a complementary relationship between public support, and firms' own private innovation investment and performance, confirming the crowding-in argument and input additionality arguments. Second, we contribute to the more limited literature on the output additionality effect of public innovation support examining both individual policy effects (e.g., Cerulli and Poti 2012; Castellacci and Lie 2015), and the output additionality of a policy mix (Guerzoni and Raiteri 2015; Rogge and Reichardt 2016). Taken together these analyses provide a deeper understanding of the range of additionality effects from both individual and combinations of

Czarnitzki and Hussinger 2018). Meanwhile, studies including Almus and Czarnitzki (2003), Kaiser (2004) and Dumont (2017) found public funding either partially or fully crowds out private innovation investment. In fact, a review of the policy evaluation literature by Zúñiga-Vicente et al. (2014) found that 48 studies across various levels of aggregation concluded complementarity between public support and private innovation investment, 15 studies reported substitution effects and 14 studies reported insignificant results.

R&D and innovation support measures. Third, we consider in some detail how contextual factors such as size, industry, knowledge and technology intensity levels, and firm productivity impact input and output additionality effects. Although a number of studies have examined the impact of tax credits and policy mix for specific types of firms along dimensions of industry and size (e.g., Colombo et al. 2011; Castellacci and Lie 2015; Minniti and Venturini 2017; Freitas et al. 2017; Jacquelyn Pless 2021), there is no study, to the best of our knowledge, that has provided such a comprehensive analysis of additionality for multiple firm-specific contexts. Differences between the additionality profiles of different types of firms suggest rather different policy prescriptions for how the innovation performance of specific firms could be enhanced to attain greater knowledge creation and social return.

Our analysis is based on the UK Innovation Survey which provides information on public R&D and innovation supports relating to direct R&D grants and indirect R&D tax incentives. The UK is a particularly interesting case study in the context of policy mix as both R&D tax incentives and R&D subsidies are significant elements of the R&D support system (Vanino et al. 2019; Jacquelyn Pless 2021). Moreover, the UK has increased its support for business innovation activities from 0.16 % of GDP in 2012 to 0.33% of GDP in 2018, ranking the UK third among OECD countries (i.e., behind France and Russia) in providing the highest level of government support to business innovation investment as a percentage of GDP (OECD, 2021). More recently, in March 2022 the UK government announced a £39.9 billion public R&D support budget for 2022-2025, the largest ever, to help to increase total R&D investment to 2.4% of GDP by 2027.

The remainder of the paper is structured as follows. Section 2 presents the conceptual framework, explaining how tax incentives or grants in isolation, and their interaction can influence R&D investment and innovation performance. Section 3 presents the related literature and hypotheses formulation. The econometric estimation strategy is described in Section 4. The data and descriptive analysis of variables are presented in Section 5. The section also provides details on both the propensity scores estimation and the matched samples and balancing test results. Section 6 presents the empirical results, detailing the policy impact for the full sample and across different types of firms. Section 7 presents conclusions, discusses some major findings, and derives the implications for policy makers. Avenues for future research are also discussed in this section.

2. CONCEPTUAL FRAMEWORK

2.1 R&D direct subsidies

Behavioural models suggest that a profit maximising firm will choose to undertake the most profitable alternatives from the range of innovation opportunities available based on their associated cost, risk and returns. R&D subsidies or grants - normally given at a percentage of the total cost of the innovation project - reduce the marginal cost of any project and the associated risk and may induce the firm to take on projects that are more marginal than otherwise (assuming that there is a ranking of investment possibilities that are eligible for grant funding). Where a firm is making an investment allocation decision across a portfolio of potential projects with different risks and returns, an R&D subsidy is also likely to mean that some eligible projects move from below to above the firm's hurdle rate of return. Firms' own financial responses to R&D subsidies may vary: crowding in may occur where subsidies induce more investment by the firm; or, particularly where resources are constrained, firms may use any subsidy to substitute (crowd-out) their own funding leading to little increase in overall R&D spending.

R&D subsidies are also generally awarded for a specific project, and this may also change projects' ranking within a firm's innovation portfolio. This may cause distortion in the relative risk and return of projects in the firm's portfolio leading to a different allocation of resources across projects than would have been the case without R&D subsidies. Biases towards or away from particular types of projects or particular technologies by those allocating R&D subsidies, or indeed funding eligibility criteria, may therefore influence which projects go ahead. Selectivity on the part of the funding committee or even grant eligibility conditions might also exert a qualitative effect where a subsidy alters the focus of firms' innovation investment. Competitive funding calls, for example, may bias investment towards new to the market – and potentially more risky innovation projects – at the cost of less risky, incremental innovation projects which may be either ineligible or unlikely to attract R&D subsidies.

Grant funding is also associated with a signalling benefit. Winning a competition for subsidy serves as a signal to other potential investors about the quality of the project and the innovative capability of the firm. This reduces the problem of information asymmetry and moral hazard for the investor. Firms might therefore use subsidised projects as a signalling mechanism to obtain complementary or future financing (Busenitz et al. 2005) amplifying the positive effects of grant funding on R&D and innovation investment. There is also the possibility that this signalling benefit might exacerbate any distortionary effect. In this situation, a grant may be sending the wrong signal in terms of portraying that project as a 'great project' thereby attracting other funds from the capital market and further distorting firms' resource allocation decisions[2]. There is also evidence that if a firm receives an R&D subsidy once it is more likely to get R&D subsidies in future. This may also be a signalling effect or reflect learning on the part of the firm in terms of how to be successful in the subsidy application process.

Once an R&D subsidy or grant has been received by a firm, and a decision made on the firms' own level of related R&D or innovation investment, questions arise as to how efficiently or effectively the investment will be used. Or, put another way, how productively will the combined public and private investment will be translated into innovation achieving output additionality. External monitoring of grant expenditure as part of the standard monitoring arrangements may, for example, mean that firms manage their innovation expenditure more carefully than if an investment was purely internally funded. However, external grant funding may also introduce financial slack into a firm leading to less stringent financial management. This may lead to a less efficient use of resources and potentially lower levels of innovative outputs and output additionality.

2.2 R&D tax incentives

R&D tax incentives or credits act by reducing firms' corporation or profit tax liabilities. As such they reduce any disincentive effect for R&D and innovation investment because of profit taxes on firms' anticipated returns from innovation. Tax incentives therefore help beneficiary firms to overcome liquidity constraints, allowing them to undertake projects at the margin of their portfolio. Nonetheless, unlike grants, tax incentives are neutral in terms of their effects across the entire portfolio of firms' projects. This means that the firm will select and invest in projects in the order of which offers the greatest private return with or without tax incentives. Tax incentives also contrast with R&D subsidies in offering no signalling benefit since tax incentives are typically available to all firms with eligible R&D expenditure.

One other advantage of tax incentives relative to R&D subsidies or grants is that tax incentives are free of any discretionary biases involved in the award of grant decisions. Instead, tax incentives are predictable subject to firms and projects meeting the eligibility

[2] Unlike profit maximising firms, policy makers are often interested in funding projects with high social return. Externalities from knowledge mean that private return and social return will differ (Griliches, 1958)

criteria and so, as most tax incentive schemes run for a long period of time, they provide a reliable base for long-term financial planning and R&D decisions. Tax incentives may therefore not only induce firms to undertake more R&D but also to engage in continuous investment in R&D activities, a factor which has itself been linked to cumulative learning and increased absorptive capacity.

2.3 Policy mix

This section focuses on how a policy mix of R&D tax incentives and R&D subsidies may impact the innovative behaviour of a firm (Flanagan et al. 2011; Rogge and Reichardt 2016). The over-all effect could be complementary, substitutionary, or neutral depending on the degree of consistency among the effects of the individual policy tools. Or, put differently, will the effect of the two instruments reinforce, contradict or weaken each other's input and output additionality effects? Complementarity in terms of policy mix could increase the likelihood of successful R&D outcomes by developing the capacity of the target firm to capitalize on all aspects of a subsidy supported project and to build up longer-term R&D capabilities to be used in other and future projects (Cunningham et al. 2013). The intuition for a positive treatment effect is as follows: tax incentives are non-competitive and designed to reduce the costs of R&D for all firms that engage in R&D activities, and thus provide liquidity for the focal firm. Although competitive and generally targeted towards reducing the cost of long-term projects with higher knowledge spillover effects, grants support also provides liquidity for the focal firm. A combination of a tax incentive and a grant would therefore mean that the firm could potentially direct the financial resource freed up by the former towards projects supported by the latter. Thus, the tax incentives may create a financial avenue for additional experimentation in the subsidised R&D activities that the firm would otherwise not have undertaken. Similarly, since both incentives lower the hurdle rate of return (through reduced R&D costs to the firm) the firm could potentially use the tax credit and any funds sourced externally to commit to projects whose rate of return may have moved from below to above the firm's hurdle rate of return.

We would therefore expect a mix of grant and R&D tax incentives to exhibit the advantages as well as the disadvantages of both policy instruments. For instance, we would expect a higher combined input and output additionality effect as the firm gets more financial support by accessing both types of support. Additionally, we might also expect a leveraging effect between the distortionary and signalling effects of a grant, while the market neutrality of a tax incentive allows the firm to take on more projects than otherwise.

3. HYPOTHESIS DEVELOPMENT

3.1 Input additionality of R&D grants

Numerous studies have evaluated the input additionality effect of R&D grants. The central question that researchers ask is whether subsidies crowd-out firms' private investment or generate an additionality effect, and crowd-in additional private investment (David et al. 2000; Guerzoni and Raiteri 2015; Radicic and Pugh 2017; Marino et al. 2016). Although most studies reject the presence of a full crowding-out effect, the results are ambiguous: while Czarnitzki and Fier (2002), Almus and Czarnitzki (2003), and Herrera and Sánchez-González (2013) find no evidence of a full crowding-out effect, Wallsten (2000), Busom (2000), and Lach (2002) find indications of a partial substitution of private R&D and innovation investments with public funding. In the same spirit, David et al. (2000) surveyed 33 pre-2000 empirical studies on public support impact, and found 16 studies reporting a complementarity effect, 11 studies reporting a substitution effect, 3 mixed results and 3 insignificant results. According to the authors, US based studies are more likely to identify substitution effects than non-US based studies. Zúñiga-Vicente et al. (2014) also reviewed 77 pre-2011 empirical studies on the effect of public R&D subsidies on firms' private R&D investment and reported mixed and inconclusive results which the authors argued could not be completely ascribed to methodological differences. Zúñiga-Vicente et al. (2014) particularly found that 48 of the studies reviewed across various levels of aggregation found public subsidies provided additionality effects to private R&D investment, 15 studies reported a substitution effect, and 14 studies reporting insignificant results. Marino et al. (2016) also examined the R&D expenditure of French firms for the 1993-2009 period and found that firms that benefited from an R&D grant invested on average 39-67 percentage points more in R&D than the control group of firms that did not receive any public funding.

Other evidence suggests that R&D input additionality decreases by grant size. Görg and Strobl (2007) specifically estimate the effects of subsidy size on Irish manufacturing firms and show that while small grants induce an additionality effect, large grants crowd-out domestic firms' private R&D investments. In the same spirit, Guellec and de la Potterie (2000) found an inverted U-shaped relationship between public subsidies and private R&D spending. Czarnitzki and Hussinger (2018) analysed the effects of public R&D funding on R&D spending and the subsequent effect on the patenting behaviour of German firms. They found that public R&D subsidies do not only induce additional R&D spending in subsidised firms (37% more than in non-subsidised firms), but also accelerate their R&D spending (27% more than in non-subsidised firms). Thereafter, the induced additional R&D

spending subsequently led to a 6.6% increase in patenting and a 9.0% increase in patent quality. Based on our conceptual framework and the reviewed empirical studies, we therefore hypothesis that:

H1: Grants in isolation will generate input additionality effects on the R&D investment of recipient firms in comparison to firms that receive no funding.

3.2 Input additionality of R&D tax incentives

Most studies that have evaluated the input additionality impact of R&D tax incentives find evidence of a positive and significant impact, although the magnitude of this positive input effect differs depending on the country, the period considered, and the econometric method applied. Hall and van Reenen (2000) reviewed the econometric evidence on the effectiveness of fiscal incentives for OECD countries' R&D activities and found evidence that suggests that, on average, a dollar in tax credit for R&D stimulates a dollar of additional R&D spending. Using a matching procedure, Sterlacchini and Venturini (2019) consider the impact of tax incentives on the R&D of manufacturing firms based in France, Italy, Spain and the UK, over the 2007 – 2009 period and find a significant increase in R&D intensity in all countries except for Spain. This effect is, however, driven only by the behaviour of small firms. Guceri (2018) also found that the UK's R&D tax policy reform which changed the definition of an SME from less than 250 employees to less than 500 employees lead to an increase in beneficiary firms' R&D spending and employment of R&D staff. Guceri (2018) also noted that the additional R&D generated through the tax relief was entirely due to an increase in the number of R&D employees in the companies' workforce.

While tax incentives may encourage non-R&D performing firms to enter R&D, they may also encourage firms to continue engaging in R&D activities. This is empirically evidenced by Arque-Castells and Mohnen (2011) who evaluated the effectiveness of the Spanish R&D tax credit on firms' decisions to enter R&D and to continue R&D activities irrespective of the future development of the tax system. The authors found that 12% of firms entered R&D because of the tax credit, and 13% continued to invest in R&D. We therefore hypothesize that:

H2: Tax incentives in isolation will generate input additionality effects on the R&D investment of recipient firms in comparison to firms that receive no funding.

3.3 Input additionality of policy mix

A recent study on the policy mix additionality effect was conducted by Guerzoni and Raiteri (2015). The authors analysis of the 27-member states of the EU, Norway and Switzerland finds a positive and significant effect of a mix of tax credits and grants on participating firms' private investment in innovation activities. Specifically, private R&D investment is 9.3 percentage points higher in firms receiving both policy supports, however, for recipients of a tax credit only and a grant only, R&D spending was respectively 2.9 and 5.3 percentage points higher. Radas et al. (2015) find similar results to that of Guerzoni and Raiteri (2015). According to Radas and colleagues' study of 175 SMEs in Croatia, direct R&D subsidies alone or a mix with R&D tax incentives strengthens SMEs' innovation activities in terms of R&D collaboration, R&D intensity and employment.

Evidence of such complementary effects is not universal, however. Applying a combination of difference-in-difference with propensity scores and exact matching techniques on 1993-2009 panel data of 12,169 French businesses, Marino et al. (2016) find evidence which suggests that while the R&D investment of firms that benefited from a grant was on average 39 percentage points more than a control group, the R&D additionality effect was only 23 percentage points for firms which benefited from a mix of grants and tax credits. The authors also recorded significant substitution of private R&D investment with public R&D funds, especially for businesses that receive medium to high values of public subsidies. Dumont's (2017) study on 5634 Belgian businesses finds similar results. Using 2003-2011 data and applying a fixed effects econometrics technique, Dumont (2017) finds that all the possible mixes of R&D subsidies with six different R&D tax credits have either an insignificant or negative effect on R&D intensity. Dumont (2017) also finds that the impact of public support on R&D intensity is dependent on the econometric specification and evaluation technique considered.

The policy mix studies reviewed indicate that the policy mix effect on R&D spending may either be stronger or weaker in comparison to that of the individual instruments. On balance, however, we suggest that:

H3a: A mix of tax incentive and direct grant will generate a positive input additionality effect on the R&D investment of recipient firms in comparison to firms that receive no funding.

H3b: A mix of tax incentive and direct grant will generate a stronger input additionality effect on R&D investment than the additionality effect of either incentive in isolation.

3.4 Output additionalities of public policies

Although evaluations of the output additionality of tax incentives have been noted as limited in the literature, several studies have evaluated the output additionality effects of R&D tax incentives. Almost all studies find positive output additionality effects regardless of whether innovation survey data or patent data is used as the measure of innovation outcomes. For example, using matching techniques, Freitas et al. (2017) conduct a firm-level analysis of the output additionality effect of R&D tax credits across three countries (i.e., Norway, Italy and France) and suggest that firms in industries with high R&D orientation exhibited stronger output additionality in terms of turnover from new products. Using a non-parametric approach, Czarnitzki et al. (2011) evaluated the effect of R&D tax credits on various innovation outputs of Canadian manufacturing firms. Firms that received tax credits exhibit significantly better scores on most innovation performance indicators: tax credits increased the probability that a firm introduced new-to-the-world and new-to-the-market products, the number of newly introduced products, and the share of sales with new products. Similar evidence of output additionality comes from Cappelen et al. (2012) who found that the Norwegian R&D tax incentive, introduced in 2002, led to the development of new production processes and new products in participating firms. Similarly, the Aralica and Botric (2013) study of the effectiveness of R&D tax incentives in Croatia found positive and significant impacts on innovation output in terms of product innovation, while Westmore (2013) examined the output additionality effects of R&D tax incentives across 19 OECD countries and found positive effects on patenting. Ernst and Spengel (2011) study on European corporations between the period of 1998-2007 found positive effects of R&D tax credit on patenting. Other studies suggest rather different profiles of additionality. For example, Bozio et al. (2014) using matching methods similar to those of Freitas et al. (2017), document that, in France, the 2008 R&D tax reform which increased the benefits of R&D tax credits led to a large increase in the number of firms claiming the public support. Evaluation of the effectiveness of the reform indicates a significant increase in R&D spending of firms that claimed the public support (i.e., input additionality) compared with firms that did not make a claim. Nonetheless, there was no evidence of output additionality in terms of the number of patents up to 2 years after the implementation of the reform. This suggests:

H4: R&D tax incentives in isolation will generate positive output additionality effects in comparison to firms that receive no such incentive.

As the study by Bozio et al. (2014) suggests, R&D support may induce input additionality but have few subsequent output additionality effects. Few studies have considered both effects, however, so evidence here is relatively limited, with the majority of studies conducted using patents as the indicator of output additionality. Czarnitzki and Hussinger (2018), for example, use a matching technique to analyse the effects of public R&D funding on R&D spending and the subsequent effect on the patenting behaviour of German firms. The authors found that public R&D subsidies not only induce additional R&D spending in subsidised firms (37% more than in non-subsidised firms), but also accelerate their R&D spending (27% more than in non-subsidised firms). Thereafter, the induced additional R&D spending subsequently led to 6.6% increase in patenting and 9.0% increase in patent quality. Beck et al.'s (2016) study of the effectiveness of Swiss public R&D subsidies found induced R&D spending in respect of the policy support had a significant effect on radical innovation in participating firms. In the same spirit, Czarnitzki and Delanote (2015) evaluated the input and output additionality of national and EU R&D subsidies for young SMEs in Germany. They find R&D subsidies induce additional R&D spending and R&D employment in both high-tech and low-tech SMEs, with the additionality effect being highest in high-tech SMEs. Their result also indicates that the induced R&D input subsequently led to a higher output additionality in terms of patenting.

H5: R&D grant in isolation will generate positive output additionality effects in comparison to firms that receive no funding.

Empirical evidence on the output additionality effects of a mix of R&D support measures is even more limited (Bérubé and Mohnen 2009; Radas et al. 2015). Bérubé and Mohnen (2009) study of Canadian manufacturing businesses is one of the few studies that consider innovation output additionality from a policy mix. Using a sample of 2,785 firms and non-parametric matching technique, the authors examine the effectiveness of Canada's public R&D grants by comparing the innovation performance of businesses that receive tax credits only with that of businesses that receive a mix of tax credits and grants. Their findings suggest that businesses that benefit from both policy instruments introduced more new products than businesses that benefit from only R&D tax credits. Receiving a policy mix also leads to more world leading innovations and more successful innovation commercialization than receiving only tax credits. In the same spirit, Radas et al. (2015) on Croatian SMEs also finds that mixing R&D tax incentives and subsidies strengthened treated firms' output additionality in terms of the number of innovations and sales from innovations. Becker et al. (2017) use panel data on UK and Spain to examine the effectiveness of regional, national and EU innovation supports on businesses innovation activities and innovation commercialization successes. Their results indicate that for both the UK and Spain, national support is correlated both with a greater probability of product/service innovation, and also the degree of novelty of product/service innovations. We therefore propose the following hypotheses in respect of output additionalities from the policy mix:

H6a: A mix of tax incentive and direct grant will generate a positive output additionality effect of recipient firms in comparison to firms that receive no funding.

H6b: A mix of tax incentive and direct grant will generate a stronger output additionality effect than the additionality effects of either incentive in isolation.

4. ECONOMETRIC METHOD

We aim to answer to the question of what would have happened to firms' R&D investment and innovation outcomes if they had not received public support. In a randomised experiment, the outcomes in treatment and control groups may often be compared directly because pre-treatment characteristics are likely to be similar (Rosenbaum and Rubin, 1983). However, in a quasi-experimental setting with an observational dataset such as that used here, there are potential issues with endogeneity and selection bias associated with the allocation decisions of funding agencies and firms' self-selection into support programmes. This implies that a direct comparison of outcomes in the treatment and control firms may be misleading since there may be systematic differences between the characteristics of firms that are exposed to the treatment and those that are not. Consequently, one cannot use the average outcome on all the non-treated firms to estimate the counterfactual effect, and instead other approaches are necessary to offset any sample selection bias. One option would be to use an appropriate instrumental variables estimator. However, it is often difficult to find and justify convincing instruments, and the data we have is no exception to this. Other estimation techniques have also been suggested to counter issues of sample selection bias including difference-in-difference estimation, regression discontinuity design (e.g., Bronzini and Piselli, 2016), fixed effect estimation and non-parametric matching estimation. Here, following Caliendo and Kopeinig (2008), Guerzoni and Raiteri (2015), and Vanino et al. (2019) we use propensity score matching (PSM) to overcome the issue of selection biases associated with allocation decisions of funding agencies and self-selection of firms into support programmes. PSM uses a control group of non-treated firms which is similar to the group of treated firms in all relevant pre-treatment characteristics, and then uses that control group to estimate the non-observable counterfactual (Caliendo and Kopeinig 2008; Guerzoni and Raiteri 2015). The advantage of the PSM methodology, like other matching methods, is that it requires no assumptions about functional forms and distributions of the error term. The downside is that it only controls for selection bias based on observables. Thus, the researcher needs to maintain the assumption that all the important characteristics driving selection into treatment are observed.

In more technical terms, we aim to estimate the causal effect of receiving public support on firm-level outcomes. Let $TREAT_i \in \{0, 1\}$ be an indicator of whether or not a firm received public support, and let PER_i^1 be the outcome if the firm received support. Also denote by PER_i^0 the performance outcome of the firm had it not received any public support. The causal effect of the receipt of public support for firm *i* is then defined as

$$PER_i^1 - PER_i^0 \qquad (1)$$

The fundamental problem of causal inference here is that PER_i^0 is unobservable. That is, the analysis can be viewed as confronting a missing-data problem. Following the micro-econometric evaluation literature (e.g., Heckman et al. 1997; Guerzoni and Raiteri 2015), we define the average treatment effect of public support on firms receiving public support (ATT) as:

$$\alpha^{TT} = E\{PER_i^1 - PER_i^0 | TREAT_i = 1\} = E\{PER_i^1 | TREAT_i = 1\} - E\{PER_i^0 | TREAT_i = 1\} \qquad (2)$$

Causal inference depends on constructing a counterfactual for the last term in Equation (2), which is the outcome that support-receiving firms would have experienced, on average, in the absence of the support. This is estimated by the performance of the control group of firms that did not receive any support. That is,

$$E\{PER_i^0 | TREAT_i = 0\} \qquad (3)$$

The estimation of Equation (3) involves the problem of selectivity. If receipt of public support is correlated with observable covariates X but Equation (3) was estimated as the average for all non-treated firms, then a biased estimate would be obtained. It is therefore crucial that a valid counterfactual that avoids the problem of selectivity is constructed. Put differently, Equation (3) should be estimated using a group of non-treated firms that are as similar as possible to the group of treated firms in terms of their observable covariates. Now, with a vector of observable covariates X at hand, there are two important assumptions necessary to achieve an unbiased estimate of the true treatment effect (see

Caliendo and Kopeinig, 2008). First, there is the need for a region of overlap (i.e., the common support assumption) between the treated and control group such that $0 < P(TREAT = 1|X) < 1$, that is, ruling out the perfect predictability of TREAT$_i$ given X (see Heckman et al. 1997). The second assumption necessary for Equation (3) to be an unbiased estimate of the treatment effect is that of conditional independence as introduced by Rubin (1977). According to the conditional independence assumption, potential outcomes (in our case the propensity to invest in R&D and innovation and innovation outcomes) are independent of selection into treatment given a set of observable covariates X which are not affected by the treatment. Practically, the conditional independence assumption permits the researcher to assume that selection into treatment is based solely on observable characteristics and that all factors that determine treatment and the outcome of interest are observable. Based on this, we can then employ matching methods to pair treated with non-treated firms which are as similar as possible on their observable characteristics X, and use the latter group to estimate the counterfactual $E\{PER_i^0|TREAT_i = 1\}$. That is, if the conditional independence assumption holds, then:

$$E\{PER_i^0|TREAT_i = 1, X\} = E\{PER_i^0|TREAT_i = 0, X\} \quad (4)$$

And, the average effect of public support on the treated firms can be estimated as:

$$\alpha^{TT} = E\{PER_i^1|TREAT_i = 1, X = x\} - E\{PER_i^0|TREAT_i = 0, X = x\} \quad (5)$$

The propensity score matching methodology ensures that the common support assumption is satisfied. This matching approach entails pairing each treated firm with a non-treated firm using similar pre-treatment characteristics in such a way that the performance of the non-treated firms can be studied to generate the counterfactual for the treated firms. Now, since matching involves comparing treated and non-treated firms across a number of observable covariates (e.g., employment, size, collaboration, skills level, regional and industry characteristics etc.), exact matching along each of these dimensions becomes impossible when dealing with so many covariates. That is, this study is confronted with the "curse of dimensionality". It is thus desirable to match the treated and non-treated firms on the basis of a single index that captures all the information from the set of covariates. Following the suggestion of Rosenbaum and Rubin (1983), we use the probability of receiving public support – the propensity score - conditional on firm specific characteristics to reduce the problem of dimensionality, so that a direct comparison between the treatment group and the control group can be made. Moreover, propensity score estimation allows the samples of treated and non-treated to be restricted to a common support by calculating the minimum and the maximum of the propensity scores of the potential control group and deleting observations in the treatment group with probabilities smaller than the minimum and larger than the maximum propensity score in the potential control group.

Consequently, we first estimate the probability of receiving public support (i.e., the ‘propensity score’) using a logit model where firm specific characteristics including employment, size, collaboration, skills level, regional and industry characteristics are used as covariates (a full list and description of all matching covariates is provided in Section 5.3 below). Now, let P_i denote the predicted probability of receiving public support for firm *i* (which is an actual support receiver). A non-treated firm *j*, which is the single closest nearest neighbour in terms of its ‘propensity score’ (i.e., P_j) to the treated firm *i* and within an imposed caliper range, is selected as a match for firm *i*. More formally, for each treated firm *i,* a non-treated firm *j* is selected such that:

$$\tau > |P_i - P_j| = \min_{j \in \{no\ support\}} \{|P_i - P_j|\} \tag{6}$$

Where τ is a pre-specified scaler, known as the caliper and reflects the similarity of the propensity score between a treated and matched control group firm[3]. Matching is here done with replacement, so that each observation in the non-treated control group can be used as a match multiple times.

In order to ensure unbiased estimates of the true effect of public support, this study also ensured the strong conditional independence assumption is satisfied with the application of the matching estimator. Fortunately, the UK innovation survey used by this study provides rich data on a wide variety of firm specific characteristics which provides a set of covariates which help to capture any non-random selection into treatment.

Apart from ensuring that both the common support and the conditional independence assumption are satisfied, we also ensure that the estimated propensity scores have a similar distribution (“balance”) in the treated and control group. Balance in individual covariates across treatment and control groups (Austin, 2009) were also ensured before finally conducting the estimation of treatment effects. Standard errors were clustered following the Abadie and Imbens (2016) methodology for the nearest-neighbour matching procedure to account for the additional source of variability introduced by the estimation of

[3] Here, since our dependent variables are all dichotomous, for each policy intervention, the chosen caliper is calculated as 20% of the standard deviation of the respective estimated propensity scores (Austin, 2011).

the propensity score (Heckman et al. 1997). Finally, as a robustness check, this study relied on kernel matching technique with a bandwidth of 0.02 to test the sensitivity of the propensity score matching method.

It is also worth noting that, before estimating the probability of receiving public support (i.e., the propensity score) and the subsequent matching that some covariates were coarsened for the purpose of matching. As suggested by Iacus et al. (2012), the aim of this process is to improve the balance of matched samples and the quality of the inferences drawn from the propensity score matching[4].

5. DATA SOURCES AND VARIABLE DEFINITIONS

For the empirical part of this study, we pooled three cross-sectional waves of the UK Innovation Survey (UKIS) which had individually been merged with the Business Structure Database (BSD) by the UK Data Service. These comprise UKIS wave 9 covering the 2012-2014 period, the UKIS wave 10 covering 2014-2016 period, and the UKIS wave 11 covering the 2016-2018 period. The UKIS database provides information on whether a firm received innovation support in the form of either a tax incentive or a direct grant during the three-year survey period. The data also provides information on firms' collaborations with external bodies and on exporting. The matched BSD provides information on firm-level employment and turnover. Our sample consists of innovating as well as non-innovating firms with 10 or more employees and in all industries. Table 1 reports the time pattern of observations in our dataset. We observe that about 85 per cent of the publicly funded observations appear only once in our data. Descriptive statistics of the variables used in our analysis are presented in Table 2 with the correlation matrix in Table A1. In total, the sample consist of 42,323 observations. 40,062 out of the total sample did not receive any public support representing (i.e., 94.6%), 1,390 (3.3%) received tax incentives only, 379 (0.9%) received grant only, and the remaining 492 (1.2%) firms received both tax and grant supports from the UK government. These statistics indicate that firms that do not receive any government support to be the largest group. Meanwhile, 18% of firms that did not receive any public support were R&D active while 21% and 15% were respectively product

[4] Specifically, we temporarily coarsened covariates including degree dummy, export dummy, year of funding dummies, region of firm location and 13 sector dummies of two-digit classification. Observations were then sorted into strata, each of which has the same values of the coarsened variables. Next, the observations in any stratum that do not include at least one treated and one control observation were pruned from the dataset. Only the observations within a stratum containing both a treated and a control unit were then kept. Subsequently, estimation of the probability of any firm participating in public funding was carried out based on a set of covariates which have been found to influence the likelihood of public fund participation in previous studies.

innovators and process innovators. A possible explanation of this is that most R&D performed in firms is either not eligible for tax benefits or that a considerable share of innovative firms do not apply for any public funding.

5.1 Outcome Variables

Researchers have operationalised innovation inputs using several indicators including R&D investment and R&D employment, and innovation outputs by measures including the probability of innovating as well as the proportion of total sales derived from products/services newly developed. We represent innovation input by a binary indicator of whether firms' have invested in internal R&D during the previous 3 years. Over the whole sample (Table 2), 22% of firms were R&D active. Innovation outcomes are represented by two main indicators: a binary measure of whether any new or improved products/services were introduced during the previous 3 years, and a binary indicator of whether any new or improved processes were introduced during the previous 3 years. Following Roper et al. (2008), and based on the recommendation of Pittaway et al. (2004) who emphasised the importance of analysing product and process innovations together, we anticipate that different policy interventions may have differential product/service and process innovation effects. Over the full sample (see Table 2), 23% of firms were product innovators whiles 17% of firms were process innovators.

5.2 Treatment variables

We use information on two public support measures for R&D and innovation in the dataset to design three different treatments and matched control groups for each treatment. There are two survey questions in the UKIS asking whether firms received financial support from the UK government during the 3-year period. The first question relates to the receipt of direct support in the form of Smart or Collaborative R&D grants, working with Catapult centres or Innovation vouchers and the second question relates to the receipt of indirect support such as R&D tax credits and patent box. The three policy treatments which were created from the two survey questions include: firms benefiting from tax incentives only, firms receiving subsidies only, and firms receiving a policy mix of tax incentives and subsidies. The control groups for all the three treatments consist of firms that did not benefit from any public support. As already indicated, of the full sample, 40,062 firms received no public support representing (94.6%), 1,390 (3.3%) received tax incentives only, 379 (0.9%) received subsidies only and 492 (1.2%) received both tax incentives and grants supports (Table 2). There are also notable overlaps between the outcome variables and the treatment variables: 91% of firms that received tax incentives only were R&D performers, 63% of firms that received grant only were R&D performers while 96% of firms that received both tax and grant supports were R&D performers. Similarly, 69% (47%) of firms that received tax-only were product (process) innovators, 52% (40%) of firms that received grant-only were product (process) innovators, while 76% (56%) of firms that received both tax and grant supports were product (process) innovators (Table 2).

5.3 Covariates used in propensity score estimation

Propensity score estimation was conducted separately for each of the three treatment scenarios using logit regression with covariates which may explain the probability of treatment. The choice of covariates for the matching attempt to capture, or be correlated with, some of the factors that funding agencies may consider when making selection decisions or firms' decisions to participate in public support (Caliendo and Kopeinig, 2008). For instance, the level of collaboration is likely to be correlated with R&D intensity and the innovation performance of the firms. We therefore include firms' external collaborations to control for the extent of firms' external knowledge sourcing activity for innovation (Roper et al. 2008; Battisti et al. 2015), and the potential effect of external knowledge spillovers (Laursen and Salter, 2006). For example, Roper et al. (2008) find evidence of a complementarity relationship between public funding for innovation and firms' ability to benefit from external knowledge sources. Firms require certain resource capabilities to successfully engage with different types of policy instruments, and for effective and efficient utilization of knowledge. We therefore include a dummy indicating whether the firm has employee(s) with a degree or higher qualification, to account for firms' workforce capabilities and knowledge utilization capacity (Roper et al. 2008). Moreover, the adoption of technology is affected by the degree that a certain innovation is related to the base of the pre-existing knowledge of its potential users (Cohen and Levinthal, 1990, p.148). Also included as a covariate is firm size, measured by the log of employment, to capture potential variations in the effects of public support across sub-groups of firms depending on size. Moreover, firm size can serve as a potential proxy for the likelihood of being financially constrained. At the same time, regulations and innovation support programmes may be specifically targeted at small firms. We also control for log employment squared. Vanino et al. (2019) for example, show that both firm size and productivity determine the likelihood of participating in publicly funded research projects. Hence, labour productivity (logged) is also included since it is likely to be correlated with the skills level of workers employed. A dummy variable indicating exporting behaviour to measure the international competitiveness of the firm is also included. Included also as controls are industry (SIC 2-digit) and regional dummies. The literature on the geography of innovation has highlighted the existence and importance of spatial dynamics in R&D activities. That is, contextual elements may impede or reinforce spillover effects and create an indirect impact of policy instruments among treated firms as well as non-treated firms (Montmartin et al. 2018). Spatial or geographic heterogeneity may also influence the reaction of focal firms to similar public interventions (i.e., firms in different territories may react differently to similar public instruments). Moreover, the impact of national R&D policies on R&D investments and innovation outcomes may vary depending on the economic structure of individual firms' geographical location (Montmartin et al. 2018). Also, high quality research institutions may be concentrated in certain regions within a country such that focal firms may be able to access unique and highly specific knowledge (Intarakumnerd and Goto, 2018). Similar to regional dummies, the set of industry dummies may capture differences in funders' preferences in granting subsidies for products produced. Time dummies are also included to control for any common macroeconomic effect on firms' innovative prospects. Finally, included as a control is an indicator measuring the scope of innovation objectives which drives firms' innovation decisions.

5.4 Propensity scores matching results

In order to account for the heterogenous likelihood of treatment participation for firms with different characteristics, we estimate a separate propensity score for each of the three policy scenarios. In Table A2, we report the propensity score estimation results stemming from a linear logit model for the general sample. Briefly, the probability of participating in either grant-only or policy mix declines with firm size, while the probability of participating in any public support (i.e., participation in either tax-only, grant-only or both) declines with labour productivity. In particular, less productive, exporting firms those with a broad scope of external collaboration, and broad innovation objectives are likely to participate in tax only support (column 2); low productivity firms with a broad scope of external collaboration, and broad innovation objectives are likely to participate in grant support only (column 4). Interestingly, in addition to being a small firm, all the factors that determine participation in tax incentives only also determine participation in policy mix (column 6). Meanwhile, firms' productivity, innovation objectives, and external collaboration prove to be critical determining factors in participation in any public funding.

Reported in Table A3 are the results of the balancing tests confirming the reliability of the matched sample and the overall quality of our matching protocol. To confirm the balancing in the propensity score, we report variance ratios comparing continuous covariates between treated and control firms in the matched samples. We also report the after-matching mean differences across the treated and control group for all the covariates used to estimate the propensity score. Where differences between treated and untreated firms were observed before matching, these are significantly reduced after matching. The bias after matching for all covariates is reduced below the 25% critical threshold, and the t-values for differences in the means are not significant. Most of the variance ratios are close to one suggesting a consistent and balanced matching, and that there are no systematic differences in the observable covariates of treated and control firms before the participation in public support.

Similarly, Figure A1 reports the graphs of the density distribution of the propensity scores estimated for the treated and control group before and after the matching procedure. We observe that, for all the three treatments, there are differences in the density distribution among the treated and control group before the matching, however, as required the common support condition appears to hold for all the treatments. After the matching procedure, the graphs show that the propensity score matching significantly reduces the imbalance in the distribution. Moreover, the high degree of overlapping indicates the quality of the matching procedure.

6. EMPIRICAL RESULTS

We examine the heterogenous impact of UK R&D support on the performance of different groups of firms. First, we estimate the general effect of tax-incentives-only, grants-only and a policy mix of both for the full sample of firms, providing tests to substantiate the robustness of the results. Second, we explore impacts across different groups of firms defined by size, productivity, technology intensity, knowledge intensity, and sector.

6.1 Full sample results

Table 3 reports the results of the effect of public funding on R&D and innovation for the full sample as well as the robustness results. Four categories of firms are considered. The group of firms that receive no public support is the control group in each case. The other three groups respectively consist of firms that receive only tax incentives, firms that receive only grant support, and firms that receive both tax incentives and grant support. The reported ATTs are the difference in average performance between the matched treatment and control groups. Since the outcome variables, internal R&D and innovation outcomes are dichotomous, the ATT's in the table represent the difference in participation rates, and therefore represent the change in percentage points of the propensity to engage in R&D or innovate after receiving a particular treatment.

The results in the top row of Table 3 indicate that receiving either tax incentives or grants only, or a policy mix has a positive and significant impact on participating firms' internal R&D investment, thus, confirming the complementarity of public funding and firms' private R&D investment. Specifically, tax-incentives-only recipient firms were 31.4 percentage points more likely to invest in R&D than firms that receive no public funding – confirming our second hypothesis. A comparison with the previous literature, which finds at the margin a dollar-for-dollar increase in R&D expenditure (Hall and Van Reenen, 2000), is difficult due to the dichotomous nature of our treatment variable. However, our results point in the direction of the general results in the literature including Bloom et al. (2002) who found that tax incentives are effective in increasing R&D investment in nine OECD countries. Similarly, the evidence of our study seems to suggest that firms that receive grant support only are 13.2 percentage points more likely to invest in R&D than firms that receive no public funding, also confirming our first hypothesis (i.e., H1). This is consistent with the evidence provided by the large body of literature (Almus and Czarrnitzki 2003; Czarrnitzki and Lopes-Bento 2014; Guerzoni and Raiteri 2015) that reports a positive and significant effect of grant support on private R&D, ruling out the crowding out hypotheses, and confirming the complementarity between public support and private investment in R&D. The results for H1 and H2 are also consistent with that of a recent meta-regression analysis of the tax incentives and grant literature, reporting significantly positive R&D investment effect from both supports (Dimos et al. 2022).

In terms of the effect of interaction between R&D grants and tax incentives, the recorded ATT of 0.27 indicates that firms that receive a policy mix are 27 percentage points more likely to invest in R&D than firms that receive no public support, also confirming hypothesis (H3a) and again in line with the many studies that found a positive and significant effect of public policy mix on the private R&D expenses of participating firms when compared with firms that receive no public support (e.g., Guerzoni and Raiteri, 2015; Neicu et al. 2016; Marino et al. 2016; Jacquelyn Pless 2021). However, comparing the strength of R&D input additionality across the three policy treatments we notice that the significant policy mix effect of 27 percentage points is smaller than the tax-incentive-only additionality of 31.4 percentage points, but larger than the grant-only additionality of 13.2 percentage points. This suggests that the effectiveness of tax incentives is slightly attenuated when used in combination with grants, or munificent financial resources, reducing the R&D investment benefit of public support (Wang and Zho, 2022). Alternatively, grants seem to enjoy a complementarity benefit from tax-incentives. That is, in terms of magnitude we do not find any support for Hypothesis 3b. This contrasts with the results of Guerzoni and Reiteri (2015), which indicates that a mix of tax credits and direct subsidies produces significantly higher R&D input additionality than the additionality of the individual policies in isolation, but supports other evidence for France (Marino et al. 2016) and Belgium (Dumont, 2017) both of which suggest that the effectiveness of public support decreases when different policy instruments interact. Our results also support another earlier study for Ireland favouring tax-incentives-only over policy mix and grant-only initiatives for achieving higher additionality in private R&D investment (Mulligan et al. 2017). Suffice to say, the confidence interval for the tax-only point estimate [0.2821, 0.3459] and that of the policy-mix [0.2226, 0.3174] overlap indicating that there is no statistically robust difference between the two estimates.

The full sample results pertaining to innovation outputs are presented in Table 3. They indicate that tax incentives, without any other public intervention, led to output additionality in respect of product innovation and process innovation. Specifically, we find support for hypothesis H5 as firms are 11.0 (10.6) percentage points more likely to introduce new and significantly improved product/services (processes) among the group of firms receiving tax-incentive-only than firms in the control group. Our results appear to be consistent with those provided by the body of literature that reports evidence of significant output additionality among R&D tax incentive receiving firms (e.g., Czarnitzki et al. 2011; Cappelen et al. 2012; Aralica and Botrić 2013). In terms of grant-support-only, we record smaller output additionality than that of tax-incentive-only since grant-only participating firms are only 5.9 (6.7) percentage points more likely have introduced new product/services (processes) than those in the control group. Nonetheless the positive and significant effect of grant-only provides further support for our hypothesis H5.

Our last treatment group concerns the possible interaction between R&D grants and R&D tax incentives in terms of innovation outputs. The results indicate that the effect of the interaction between the two policy tools is always significantly positive (confirming H6a) and considerably higher than the two policy instruments in isolation (confirming H6b). Specifically, 12.8 (13.8) percentage points more firms in the policy mix recipients' group than the control group undertook product/service (process) innovation. This evidence suggests that the interaction of grant and tax incentives creates stronger additionality in innovation than those generated by either of the instruments in isolation. This complementarity between the output additionality effects of tax incentives and grants contrasts markedly with the slight attenuation effect noted earlier in terms of input additionality, and is consistent with the theoretical analysis of Flanagan et al. (2011) and Rogge and Reichardt (2016) which suggests the complementarity effects of mixing policy instruments. A similar result was found by Bérubé and Mohnen (2009) who showed that about 80% of Canadian manufacturing firms that used a mix of tax credits and grants recorded having undertaken at least one innovation while about 72% did so among firms that used tax credit only support.

Comparing the ATTs for input and output additionality suggests significantly stronger input additionality for each type of policy support individually, as well as the policy mix. Notably, the difference between input and output additionality for tax incentives and the policy mix is larger than that for grant support: tax incentives (and the related policy mix) achieve strong input additionality, but this does not fully translate into innovation outputs; grant support achieves weaker input additionality but has more consistent output additionality effects. For each support measure (and the policy mix) we therefore see stronger input than output effects, potentially suggesting innovation productivity (i.e., the translation of innovation inputs into outputs) is lower where public support is received. This may simply reflect less effective use of innovation resources but may also be due to a focus on more risky or radical innovation projects and higher levels of project failure or abandonment.

Robustness tests using an alternative kernel matching technique produce very similar ATT's (see column 5 – column 7 of Table 3) and have consistent statistical significance when considering all the three treatment models.

6.2 Firm heterogeneity effects

Previous research has found that the impact of public support on firms' R&D and innovation performance may vary depending on other firms' characteristics (e.g., see Vanino et al. 2019; Czarnitzki and Lopes-Bento 2014; Dimos and Pugh 2016). We therefore evaluate input and output additionality effects across firm size, industry, technology, and productivity level (Tables 4-6)[5]. In each case a separate matching exercise was undertaken to develop relevant control groups, with results very similar to those reported in Table A1 and Figure A1.

In terms of business size, each of the three policy treatments has a positive and significant input additionality impact on R&D investment regardless of firm size, although the effect of both tax-incentives-only and grant-only is higher for small firms (Becker 2015; Castellacci and Lie 2015; Vanino et al. 2019). Reflecting our full sample results, output additionality effects related to product and process innovation are smaller in size across all firm

[5] Detailed results for each group of firms are included in Annex 2, Table 6.

sizebands, and for grant-only often insignificant (Table 4). Output additionality effects of tax-incentives-only are similar for small and medium-large firms (Petrin and Radicic, 2023), while we find significant output additionality only for process innovation among small firms, where the output additionality of a policy mix is also notably stronger in smaller firms (Table 4). This may reflect the greater benefit of grant support for small business who often experience greater financial and capability constraints.

Comparing input and output additionalities and policy mix effects between manufacturing and services companies suggests a rather similar pattern (Table 5)[6]: input additionality effects prove larger than output additionality effects, with grant-only support having no significant output additionality effects. This result is similar to that of previous literature suggesting greater input additionality effects of a tax credit among participating service firms (Castellacci and Lie, 2015) and smaller R&D support effect among R&D performers (Dimos et al. 2022). Also, a similar result was found by Petrin and Radicic (2023) indicating positive effects of tax credit and no effect of grant, on both product and process innovation, among participating Spanish Manufacturing businesses. Differentiating between manufacturing and service firms, input additionality effects are typically larger in services than manufacturing, with some evidence of complementarity in output additionality effects for both manufacturing and services (Table 5). This reflects Bérubé and Mohnen's (2009) finding that Canadian manufacturing firms that received a mix of grants and tax credits experienced a stronger effect on product innovation than they experienced from tax credits in isolation. Tax only and policy-mix output additionality effects are also larger in services, although again notably lower than the related input additionality effects (Table 5).

Finally, we examine input and output additionality effects across the productivity distribution. Irrespective of firms' productivity level, both tax-incentives-only and policy-mix significantly promote participating firms' R&D investment, although the effect of tax-incentives-only is greater in lower productivity firms (Becker 2015; Vanino et al. 2019). Again, we see some attenuation effect, with input additionality from the policy mix below that of tax-incentives-only for all but the lowest productivity firms (Table 6). In terms of output additionality, the results indicate a significant and positive effect of tax-incentives-only and policy mix on product innovation among all firms but the lowest quartile of the productivity distribution (Table 6, Columns 2, 4, 5, 7, 8, 10 and 11). One interpretation is that low productivity firms are less effective in translating innovation inputs into innovation

[6] Manufacturing sectors includes all industries with SIC2007 code:10-33. Services sector includes industries with SIC2007 code: >=45

outputs, due to their limited management and innovation processes (Gahan et al. 2021). Again, grant-only support has no significant output additionality effect for either product or process innovation at any point in the productivity distribution (Table 6, Columns 3, 6, 9 and 12).

7. DISCUSSION AND CONCLUSION

Firms increasingly rely on public support for their innovation activities. Previous research on the effectiveness of public support often concentrates on analysis of individual policies (e.g., Arque-Castells and Mohnen 2011; Czarnitzki and Hussinger 2018; Sterlacchini and Venturini 2019). This is even though firms often receive multiple public supports which interact with one another to create either a complementary, trade-offs or neutral effect. This has led to a call to researchers for analysis of the interaction effects of policy mixes that firms receive to avoid a misattribution of policy benefits (Flanagan et al. 2011; Rogge and Reichardt 2016; Lenihan and Mulligan 2018). Studies also either tend to consider input or output additionality in isolation (e.g., Guerzoni and Raiteri 2015; Radas et al. 2015; Marino et al. 2016; Freitas et al. 2017) providing little insight into relative levels of additionality, and whether any innovation input additionalities firms achieve is translated into enhanced innovation outputs. The limitation in the number of empirical studies considering both the input and output additionality of policy mix has been attributed to the lack of relevant datasets (e.g., Guerzoni and Raiteri 2015; Rogge and Reichardt 2016; Lenihan and Mulligan 2018). Here, we address these three research gaps using data from three waves of the UK Innovation Survey and with propensity scores matching (coarsened exact matching) techniques. We identify four groups of key findings.

First, in terms of R&D input additionality we find evidence of strong and positive tax-incentive-only, grant-only and policy-mix effects on R&D investment (Czarnitzki et al. 2011; Cappelen et al. 2012; Aralica and Botrić 2013). This is consistent with a large literature which emphasises the potential for policy support to crowd-in private sector R&D investment (Arque-Castells and Mohnen 2011; Zúñiga-Vicente et al. 2014; Becker 2015; Marino et al. 2016; Guceri 2018; Sterlacchini and Venturini 2019). Notably, however, input additionality effects from tax-incentives-only are consistently around twice as large as those of grants, and also larger than policy-mix impacts, suggesting some attenuation or substitution effects between the input additionality of grants and tax-incentives. This picture is consistent across almost all sample sub-groups in our data and supports the conclusions of other studies for France (Marino et al. 2016) and Belgium (Dumont 2017). This may also relate to other evidence which suggests an inverted-U shape relationship between public funding and private R&D spending (Guellec and de la Potterie, 2000), i.e., at low or very high levels of subsidy/funding crowding-in effects may be weaker.

Second, product and process innovation output additionality is consistently positive from tax-incentive-only, and the related policy-mix (Bérubé and Mohnen 2009; Czarnitzki et al. 2011; Cappelen et al. 2012; Aralica and Botric 2013; Radas et al. 2015; Freitas et al. 2017). However, grant-only output additionality effects are notably smaller in scale and statistically much weaker. Here, however for our overall sample and some groups of firms we also observe complementarity between tax and grant measures leading to stronger policy-mix additionality (Berube and Mohnen 2009; Flanagan et al. 2011; Rogge and Reichardt 2016). In other words, in terms of output additionality the effects of grant support and tax incentives are mutually reinforcing. This reflects some of the limited international evidence from Canada (Bérubé and Mohnen, 2009) and Croatia (Radas et al. 2015).

Third, we find a, perhaps surprising, difference in the scale of input and output additionality effects for tax incentives-only and the related policy mix: input additionality effects are consistently larger – 2-3 times – the scale of output additionality effects. In other words, while tax incentives, grants and a policy-mix are very likely to achieve input additionality – crowding in private R&D investment – they are significantly less likely to result in output additionality – i.e., product/service or process innovation. In part this difference in levels of additionality might be anticipated given the technical and commercial risks involved in innovation. Rhaiem and Amara (2021), for example, summarise numerous academic studies which estimate the proportion of innovative projects which are abandoned wholly or in part to be between 40% and 90 per cent. While this alone might explain the difference in our estimates of input and output additionality, this may also reflect the impact of tax incentives and grant support on firms' selection of innovation projects. Both may reduce the costs of innovating and therefore encourage firms to undertake more risky or perhaps more challenging research projects (Mulligan et al. 2022).

Finally, sample sub-groups suggest some interesting findings. Input additionalities are, for example, strongest in lower productivity firms although these firms then struggle to generate significant output additionalities (Becker 2015; Vanino et al. 2019). Again, this may reflect the commercial and technical challenges involved in innovation (Rhaiem and Amara, 2021). By contrast, while higher productivity firms see lower input additionality this does eventually translate into higher and significant output additionalities (Gahan et al. 2021).

Our results suggest a number of implications. For example, in terms of policy evaluation our analysis suggests that using the extent of input additionality as an indicator could provide misleading results. As levels of input additionality are significantly greater than that of output additionality, policy assessments based purely on input additionality may over-estimate policy effectiveness. In addition, as the relationship between input and output additionality differs significantly between groups of firms (e.g., those with differential productivity) input additionality indictors alone provide a distorted view of potential innovation outcomes. Including output additionality indicators in R&D and innovation policy evaluations is likely to require longer evaluation timelines than are often adopted. Other implications relate more directly to our policy mix results, which suggest mild substitution in terms of input additionality but complementarity in terms of output additionality. Here, further research seems necessary to understand why these contrasting pattens are emerging. Qualitative studies of how different firms make their project selection and policy participation decisions could provide detailed insights. More detailed quantitative data which allows us to identify the value of support that firms receive may also provide additional insight. Exploring administrative data on the amount of R&D tax incentives and R&D grant supports available to firms may help with the analysis of whether and where government may be under- or over-subsidising firms' innovation activity.

Another potentially fruitful avenue for future research would be to explore how firms' engagement with R&D grant and tax incentives changes over time. With future innovation surveys, it may be possible to examine whether more long-term engagement with public R&D support increases output additionality and/or changes the relationship between input and output additionality. Our data is also constrained concerning information on the different phases of firms' innovation development. We are thus unable to examine whether the grant supported firms are for instance still undertaking experimental developments to validate their new and improved products and/or processes. Access to datasets with more comprehensive information on the various supports that firms receive as well as information on the different stages of firms' innovation development may present an excellent analytical advantage for empirical studies. Finally, the policy treatment considered in this study used firms that did not receive any public support as the control group. This approach does not directly examine how a policy mix performs vis-à-vis tax incentives and grants in isolation. Future research could extend this research by using participation in tax-incentive-only and grant-only supports as two distinct control groups for participation in a mix of both supports.

Table 1: Data Observational pattern

Full sample			Treated Sample		
Time Pattern	% Observations	cum. % observations	Time Pattern	% Observations	cum. % observations
100	28.5	28.5	100	36.4	36.4
001	20.9	49.4	001	26.8	63.2
010	16.2	65.6	010	21.8	**84.9**
011	11.5	77.1	110	5.4	90.3
111	9.7	86.8	011	4.6	94.9
110	7.5	94.3	101	2.8	97.6
101	5.7	100.0	111	2.4	100.0

NOTE: Time pattern shows the share of observations that are available in the full sample and share of observations for which public funding recipients are available (denoted by 1) and not available (denoted by 0) for each wave in the period of the three surveys.

Table 2: Descriptive statistics across treatment participation

	Full Sample			No support			Tax incentive only			Grant only			Both tax and grant		
	# firms	Mean	Std.	# firms	mean	SD	# firms	Mean	SD	# firms	Mean	SD	# firms	mean	SD
Internal R&D	42,323	0.22	0.41	40,062	0.18	0.38	1,390	0.91	0.29	379	0.63	0.48	492	0.96	0.20
Product innovation	42,323	0.23	0.42	40,062	0.21	0.40	1,390	0.69	0.46	379	0.52	0.50	492	0.76	0.43
Process innovation	42,323	0.17	0.37	40,062	0.15	0.36	1,390	0.47	0.50	379	0.40	0.49	492	0.56	0.50
Employment (log)	42,323	4.18	1.48	40,062	4.17	1.48	1,390	4.44	1.36	379	4.25	1.58	492	4.08	1.41
Lab. productivity (log)	42,273	4.46	1.27	40,017	4.46	1.27	1,385	4.65	1.16	379	4.42	1.20	492	3.97	1.69
Innovation objective breadth	42,323	4.08	5.10	40,062	3.74	4.98	1,390	10.16	2.93	379	9.58	3.87	492	10.64	2.43
Collaboration breadth	42,323	1.12	2.23	40,062	0.98	2.11	1,390	3.19	2.58	379	3.72	2.93	492	4.97	2.61
Degree	37,802	0.55	0.50	35,541	0.53	0.50	1,390	0.92	0.27	379	0.80	0.40	492	0.95	0.21
Export	42,323	0.29	0.45	40,062	0.26	0.44	1,390	0.72	0.45	379	0.48	0.50	492	0.80	0.40

Table 3: Impact of participation in public support on firms' innovation performance - Full sample and robustness

	Full sample - N-N matching			Full sample - Kernel matching		
	Tax only	Grant only	Both	Tax only	Grant only	Both
Internal R&D	0.314***	0.132***	0.270***	0.315***	0.152***	0.270***
std. Err.	(0.016)	(0.035)	(0.024)	(0.010)	(0.026)	(0.017)
Product innov.	0.110***	0.059*	0.128***	0.141***	0.046*	0.163***
std. Err.	(0.019)	(0.036)	(0.034)	(0.014)	(0.027)	(0.024)
Process innov.	0.106***	0.067*	0.138***	0.093***	0.056**	0.134***
std. Err.	(0.020)	(0.038)	(0.038)	(0.014)	(0.027)	(0.026)
No. Treated	1,377	371	486	1377	372	487

Robust standard errors are in parentheses. ** * (**, *) signify 1% (5%, 10%) level of significance. Number of Control observations equals number of treated observations

Table 4: Impact of participation in public support on UK firms' innovation performance across firms' size distribution

	Small (10 - 49 employment)			Medium - large (50+ employment)		
	Tax only	Grant only	Both	Tax only	Grant only	Both
Internal R&D	0.348***	0.123**	0.238***	0.279***	0.099**	0.245***
std. Err.	(0.027)	(0.056)	(0.035)	(0.019)	(0.045)	(0.033)
Product innov.	0.128***	0.037	0.100*	0.125***	0.040	0.174***
std. Err.	(0.031)	(0.057)	(0.052)	(0.023)	(0.049)	(0.043)
Process innov.	0.117***	0.148***	0.184***	0.104***	-0.005	0.087 *
std. Err.	(0.033)	(0.054)	(0.052)	(0.024)	(0.047)	(0.051)
No. Treated	469	162	239	906	202	241

Robust standard errors are in parentheses. ** * (**, *) signify 1% (5%, 10%) level of significance. Number of Control observations equals number of treated observations

Table 5: Impact of participation in public support on firms' innovation performance - Manufacturing and service industries

	Manufacturing			Manufacturing - HT			Manufacturing - LT		
	Tax only	Grant only	Both	Tax only	Grant only	Both	Tax only	Grant only	Both
Internal R&D	0.236***	0.096*	0.202***	0.195***	-0.082	0.113**	0.264***	0.296***	0.364***
std. Err.	(0.025)	(0.057)	(0.039)	(0.032)	(0.060)	(0.048)	(0.035)	(0.075)	(0.067)
Product innov.	0.145***	0.067	0.168***	0.153***	0.122	0.148**	0.136***	0.074	0.218**
std. Err.	(0.032)	(0.067)	(0.051)	(0.043)	(0.083)	(0.068)	(0.046)	(0.102)	(0.084)
Process innov.	0.137***	0.087	0.127**	0.172***	0.082	0.148**	0.107**	0.111	0.109
std. Err.	(0.032)	(0.066)	(0.058)	(0.045)	(0.096)	(0.070)	(0.046)	(0.105)	(0.099)
No. Treated	504	104	173	261	49	115	242	54	55
	Service			KIS			Less-KIS		
	Tax only	Grant only	Both	Tax only	Grant only	Both	Tax only	Grant only	Both
Internal R&D	0.355***	0.112***	0.304***	0.326***	0.134**	0.288***	0.479***	0.0549	0.346***
std. Err.	(0.020)	(0.043)	(0.036)	(0.024)	(0.053)	(0.037)	(0.044)	(0.068)	(0.112)
Product innov.	0.104***	0.062	0.141***	0.104***	-0.024	0.102**	0.130***	0.154	0.385***
std. Err.	(0.023)	(0.048)	(0.041)	(0.027)	(0.061)	(0.043)	(0.048)	(0.079)	(0.130)
Process innov.	0.068***	0.050	0.163***	0.092***	-0.018	0.164***	0.060	0.110	0.192
std. Err.	(0.024)	(0.043)	(0.049)	(0.028)	(0.050)	(0.050)	(0.045)	(0.072)	(0.151)
No. Treated	859	258	306	644	164	274	215	91	26

Robust standard errors are in parentheses. ** * (**, *) signify 1% (5%, 10%) level of significance. Number of Control observations equals number of treated observations

Table 6: Impact of participation in public support on firms' innovation performance across productivity distribution (quartiles)

	1st quartile			2nd quartile			3rd quartile			4th quartile		
	Tax only	Grant only	Both	Tax only	Grant only	Both	Tax only	Grant only	Both	Tax only	Grant only	Both
Int. R&D	0.341***	0.207***	0.362***	0.320***	0.0778	0.151***	0.294***	0.086	0.242***	0.266***	0.136*	0.155***
std. Err.	(0.031)	(0.078)	(0.046)	(0.032)	(0.069)	(0.041)	(0.032)	(0.064)	(0.049)	(0.033)	(0.072)	(0.050)
Pdt. Inno.	0.058	0.126	-0.017	0.163***	-0.100	0.151**	0.113***	-0.065	0.158**	0.140***	0.011	0.103*
std. Err.	(0.039)	(0.077)	(0.076)	(0.039)	(0.071)	(0.074)	(0.038)	(0.071)	(0.063)	(0.040)	(0.076)	(0.058)
Proc. Inno.	0.070*	0.103	0.155*	0.058	0.033	0.176**	0.096**	0.022	0.192***	0.132***	-0.114	-0.009
std. Err.	(0.040)	(0.081)	(0.084)	(0.040)	(0.073)	(0.068)	(0.039)	(0.081)	(0.069)	(0.038)	(0.066)	(0.065)
# Treated	343	87	116	344	90	119	344	93	120	342	88	116

Robust standard errors are in parentheses. ** * (**, *) signify 1% (5%, 10%) level of significance. Number of Control observations equals number of treated observations

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ANNEX

Table A1: Correlation Matrix

	Variable	Obs.	1	2	3	4	5	6	7	8	Tax only (0/1) (Obs: 41, 452)	Grant only (0/1) (Obs: 40,441)	Tax and grant (0/1) (Obs: 40,554)
1	Internal R&D (0/1)	42,323									0.33	0.11	0.22
2	Product innovation (0/1)	42,323	0.49								0.21	0.08	0.15
3	Process innovation (0/1)	42,323	0.36	0.40							0.16	0.15	0.12
4	Employment (log)	42,323	0.09	0.05	0.06						0.03	0.01	-0.01
5	Lab. productivity (log)	42,273	0.06	0.04	0.03	0.07					0.03	-0.01	-0.04
6	Innovation objective breadth (0-12)	42,323	0.59	0.55	0.44	0.09	0.47				0.23	0.11	0.15
7	Collaboration breadth (1-10)	42,323	0.44	0.41	0.33	0.07	0.38	0.61			0.18	0.12	0.20
8	Degree (0/1)	37,802	0.31	0.24	0.19	0.14	0.48	0.41	0.28		0.15	0.06	0.10
9	export (0/1)	42,323	0.33	0.25	0.16	0.10	0.33	0.30	0.19	0.28	0.18	0.05	0.13

Table A2: Logit regression results for treatment participation - Full sample

	Tax only	s.e.	Grant only	s.e.	Both	s.e.
Log employment	0.162	(0.1270)	-0.602**	(0.1910)	-0.474*	(0.2060)
(Log employment) ²	-0.0139	(0.0132)	0.0599**	(0.0194)	0.0366	(0.0215)
Log lab. Productivity	-0.0580*	(0.0282)	-0.116*	(0.0502)	-0.388***	(0.0405)
Innovation obj. breadth	0.148***	(0.0096)	0.126***	(0.0170)	0.117***	(0.0199)
Collaboration breadth	0.405***	(0.0380)	0.503***	(0.0730)	0.764***	(0.0725)
(Collaboration breadth) ²	-0.0396***	(0.0045)	-0.0339***	(0.0081)	-0.0499***	(0.0074)
Degree (0/1)	0.041	(0.1130)	-0.652***	(0.1720)	-0.399	(0.2670)
Export (0/1)	0.708***	(0.0765)	-0.0113	(0.1430)	0.994***	(0.1460)
Intercept	-2.827***	(0.4870)	-0.011	(0.8910)	-1.354	(1.3300)
Sector: χ^2(p-value)	212.84	(0.0000)	60.8	(0.0000)	66.75	(0.0000)
Region: χ^2(p-value)	41.24	(0.0000)	35.92	(0.0000)	60.98	(0.0000)
Year: χ^2(p-value)	9.11	(0.0105)	17.85	(0.0001)	22.38	(0.0000)
Observations	17,380		11,146		8,654	
Pseudo-R^2	0.1719		0.1583		0.2763	
log likelihood	-3985.06		-1377.97		-1366.75	

Robust standard errors are in parentheses. ** * p< 0.001, ** p<0.01, * p<0.05.
χ^2 values indicate test on joint significance of sector, regional and year dummies.

Table A3: Matching average balancing test

Tax only	Mean			Bias	t-test			Variance
	treated	control		Perc.	t-value	p-value		Ratio
Log employment	4.4383	4.4575		1.4	0.37	0.711		0.99
(Log employment) ²	21.55	21.732		1.4	0.37	0.715		1.02
Lab. Productivity (log)	4.651	4.6204		2.6	0.7	0.484		1.06
Innovation obj. breadth	10.16	10.322		3.7	1.39	0.165		0.86*
Collaboration breadth	3.183	3.2244		1.7	0.41	0.679		0.93
(Collaboration breadth) ²	16.784	17.544		3.9	0.91	0.363		0.95
Degree	0.91794	0.92593		2.4	0.78	0.435		.
Export	0.71823	0.69354		5.2	1.42	0.155		.
Ps R^2	LR-chi^2	p>chi^2	MeanBias	MedianBias	B	R	Treated	Untreated
0.002	8.88	0.353	2.80	2.50	11.40	0.90	1,377	1,377

Grant only	Mean			Bias	t-test			Variance
	treated	control		Perc.	t-value	p-value		Ratio
Log employment	4.2254	4.1631		4.2	0.55	0.585		0.98
(Log employment) ²	20.233	19.767		3.3	0.41	0.681		0.97
Lab. Productivity (log)	4.4018	4.4261		2.1	0.27	0.788		0.87
Innovation obj. breadth	9.5553	9.3208		5	0.79	0.428		0.87
Collaboration breadth	3.7008	3.469		8.8	1.09	0.276		1.05
(Collaboration breadth) ²	22.251	20.197		9.7	1.13	0.257		1.08
Degree	0.80863	0.79245		3.9	0.55	0.582		.
Export	0.47709	0.45013		5.4	0.74	0.462		.
Ps R^2	LR-chi^2	p>chi^2	MeanBias	MedianBias	B	R	Treated	Untreated
0.003	2.82	0.945	5.3	4.6	12.3	1.10	371	371

Both tax and grant	Mean			Bias	t-test			Variance
	treated	control		Perc.	t-value	p-value		Ratio
Log employment	4.078	4.1669		6.4	1.01	0.31		1.09
(Log employment) ²	18.57	19.148		4.4	0.69	0.491		1.16
Lab. Productivity (log)	4.0301	4.0689		2.7	0.37	0.713		0.78*
Innovation obj. breadth	10.648	10.883		5.6	1.48	0.139		0.93
Collaboration breadth	4.9342	4.7428		7.5	1.15	0.249		1.03
(Collaboration breadth) ²	31.107	29.08		9	1.26	0.208		1.09
Degree	0.95473	0.94856		2.4	0.45	0.654		.
Export	0.79835	0.81893		4.7	0.81	0.415		.
Ps R^2	LR-chi^2	p>chi^2	MeanBias	MedianBias	B	R	Treated	Untreated
0.006	8.35	0.400	5.3	5.1	18.6	1.09	486	486

Figure A1. Distribution of the propensity scores of treated and non-treated groups before and after matching

Unmatched Matched

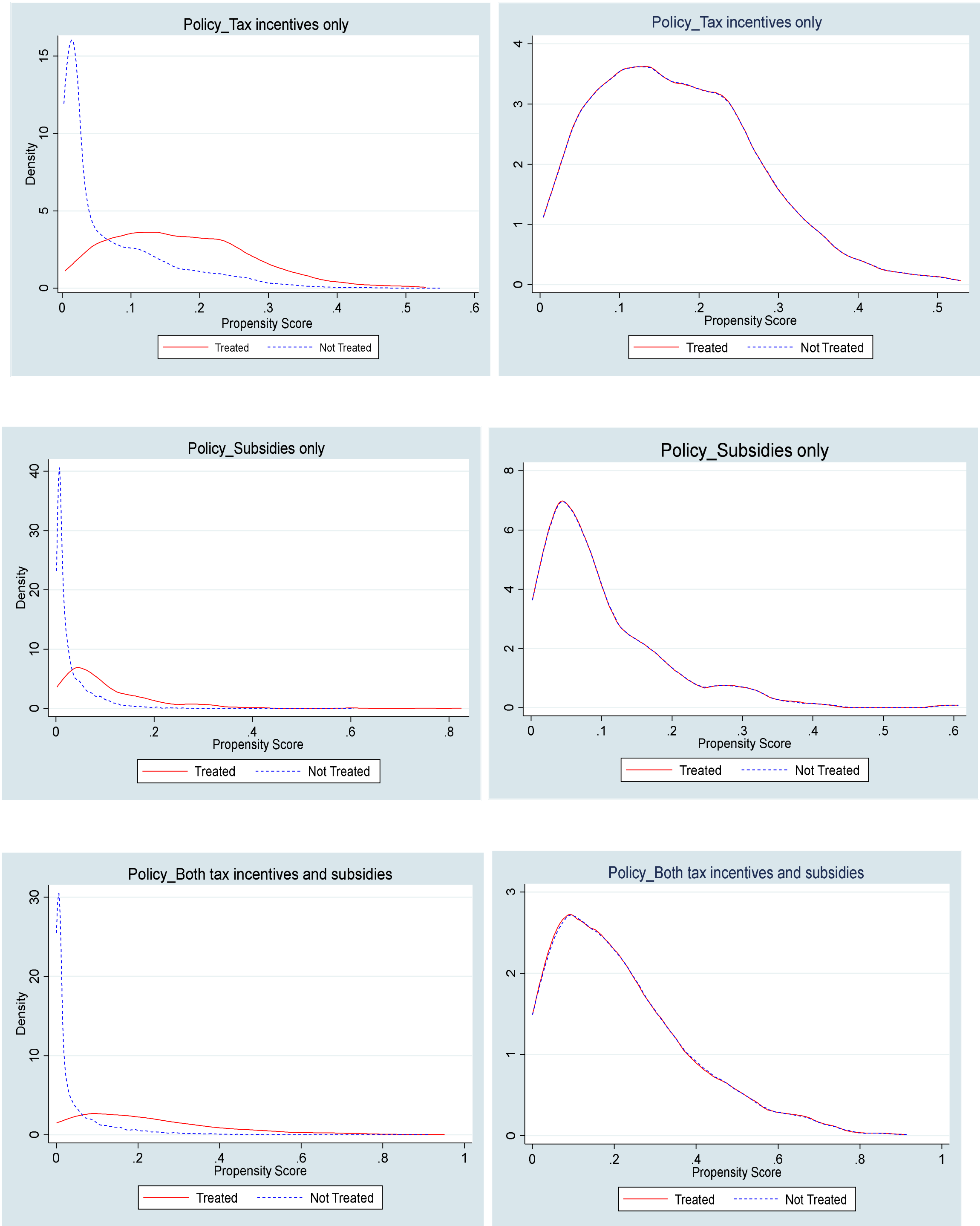

Table A4: Summary of ATT results by type of firm

	Internal R&D investment			Product innovation			Process innovation		
	Tax only	Grant-only	Both	Tax only	Grant-only	Both	Tax only	Grant-only	Both
Full results	0.314***	0.132***	0.270***	0.110***	0.059*	0.128***	0.106***	0.067*	0.138***
Small	0.348***	0.123**	0.238***	0.128***	0.037	0.100*	0.117***	0.148***	0.184***
Medium-large	0.279***	0.099**	0.245***	0.125***	0.040	0.174***	0.104***	-0.005	0.087 *
Manufacturing	0.236***	0.096*	0.202***	0.145***	0.067	0.168***	0.137***	0.087	0.127**
Services	0.355***	0.112***	0.304***	0.104***	0.062	0.141***	0.068***	0.050	0.163***
KIS	0.326***	0.134**	0.288***	0.141***	0.104***	-0.024	0.163***	0.092***	-0.018
LKIS	0.479***	0.0549	0.346***	0.130***	0.154	0.385***	0.060	0.110	0.192
Productivity frontiers									
1st quartile (Low)	0.341***	0.207***	0.362***	0.058	0.126	-0.017	0.070*	0.103	0.155*
2nd quartile	0.320***	0.0778	0.151***	0.163***	-0.100	0.151**	0.058	0.033	0.176**
3rd quartile	0.294***	0.086	0.242***	0.113***	-0.065	0.158**	0.096**	0.022	0.192***
4th quartile (High)	0.266***	0.136*	0.155***	0.140***	0.011	0.103*	0.132***	-0.114	-0.009

Note: ** * (**, *) represent 1% (5%, 10%) level of significance.

ERC
Enterprise Research Centre

Centre Manager
Enterprise Research Centre
Warwick Business School
Coventry, CV4 7AL
CentreManager@enterpriseresearch.ac.uk

Centre Manager
Enterprise Research Centre
Aston Business School
Birmingham, B1 7ET
CentreManager@enterpriseresearch.ac.uk

Economic and Social Research Council
Innovate UK
wbs
Aston University
Queen's University Belfast
Department for Business & Trade
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