Assessing the business performance effects of receiving publicly-funded science, research and innovation grants

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ABSTRACT

UK Research Councils including Innovate UK spend around £3bn pa on supporting research. Here, we provide the first comprehensive assessment of these research grants on the performance of participating UK firms. Using data on funding and partnership from Gateway to Research on all funded projects by the UK Research Councils over the 2004 to 2016 period and business performance data from the Business Structures Database we have applied a difference-in-differences propensity score matching technique to evaluate the performance of UK firms who participated in publicly-funded research projects. Our analysis suggests four key conclusions. First, firms who participated in research projects funded by UK research councils grew their turnover and employment 5.8-6.0 per cent faster in the three years after the project, and 22.5-28.0 per cent faster in the six years after the project, than similar firms which did not receive support. Second, the impact of participating in projects is larger for firms in high-tech manufacturing and knowledge intensive services. Third, we find evidence that the impact of participating in projects is larger for small firms and those with lower starting productivity (turnover per employee). Growth impacts on firms in the top quartile of the productivity (turnover per employee) distribution are small. Fourth, support for projects relevant to businesses is provided largely by EPSRC and Innovate UK. Participation in projects funded by these organisations increases both employment and turnover growth in the short and medium terms with only marginal differences in their impact. Our results have implications for the extent and targeting of future Research Council funding.

Our analysis is subject to a number of caveats. First, data limitations mean that we measure economic impacts using turnover and employment data rather than value added per worker or hour worked. Secondly, at this point we only consider the direct impacts on firms. Spillovers or multiplier effects may significantly enlarge these effects; displacement may reduce them. Both will be considered in a future study. Thirdly, data linking and the timing of some grant awards in recent years mean we are able to consider growth effects for only around two-thirds of firms which participated in publicly funded science and innovation projects.

Keywords: Public support; R&D; innovation; research council; UK.

CONTENTS

1. INTRODUCTION

Through its publicly funded Research Councils the UK invests around £3bn annually in supporting scientific research. This investment is set to increase sharply in future years as the Industrial Strategy Challenge Fund – announced in the 2016 Autumn Statement – is steadily expanded to an additional £2bn in 2020. To date, assessments of the impact of this public investment have been partial and largely case-based. Where quantitative assessments of impact have been attempted they have often relied on the limited information available in innovation surveys, or focused on specific elements of the public science system. Several previous studies add to the substantial evidence from a range of countries on the positive role of research grants, subsidies and tax credits in helping firms to innovate successfully (Zuniga-Vicente et al. 2014; Becker, 2015; Dimos and Pugh, 2016). A more limited strand of the literature looked instead at the impact of R&D subsidies and programs on the overall performance of firms, taking into consideration turnover or productivity growth (Belderbos et al., 2004; Cin et al., 2017). Even though this literature has resulted in quite mixed results, it has generally supported the existence of a positive relationship between R&D public support, innovation and firms' growth (Aguiar and Gagnepain, 2017).

In this study we analyse for the first time the comprehensive effect of public support to innovation, assessing the impact of engaging with publicly-funded research and science on the performance of UK firms. We draw on funding and partnership data from "Gateway to Research" (GtR) portal which provides information on funding provided by all of the UK Research Councils (including Innovate UK) over the 2004 to 2016 period as well as the characteristics of the partners involved in each research project. Data on business performance is taken from the Business Structures Database which provides longitudinal data on business performance for all UK firms in terms of employment, turnover and productivity (turnover per employee) growth.

Our study responds to the call by Scandura (2016) for more extensive research on the performance effects of publicly funded scientific research. We extend the existing evidence base in several ways. First, we provide the first comprehensive assessment of the business impacts of public science investments in the UK. Second, as we have data from each of the Research Councils we are able to evaluate the impact on firms which participated in projects funded by different organizations, comparing for instance the differences between firms engaged in more basic science projects (including use-inspired basic) funded primarily by the EPSRC and those involved in more applied projects funded by Innovate UK. Third, we are also able to explore the potential effect of repeated participation, according to the value of research grants. Fourth, we are able to compare levels of impact between sectors, firm scale, productivity - proxied by turnover per employee - and regional distribution. Fifth, thanks to the longitudinal data on both firm performance and grant receipt, we are able to assess time lags between firms' project participation and any impacts on firms' growth in the short and medium term. Finally, our study responds to the call by various national and international organisations for more extensive access to and use of administrative data for research, including the OECD[1], Card et al (2011) addressing the National Science Foundation[2], ISTAT[3] and the UK Data Forum[4].

We employ a difference-in-difference, propensity score matching technique to analyse the differences in performance between UK firms who participated in funded research projects and a matched comparator group of firms which received no support. Comparing their performance before and after the research projects we are able to estimate the causal effect of publicly-funded research on

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[1] OECD (2013), 'New Data for Understanding the Human Condition: International Perspectives', OECD Global Science Forum Report on Data and Research Infrastructure for the Social Sciences, available at http://www.oecd.org/sti/sci-tech/new-data-for-understanding-the-human-condition.pdf

[2] Card, D., Chetty, R., Feldstein, M. and Saez, E. (2011), 'Expanding Access to Administrative Data for Research in the United States', written for the NSF call for white papers on 'Future Research in the Social, Behavioral & Economic Sciences, available at: https://eml.berkeley.edu/~saez/card-chetty-feldstein-saezNSF10dataaccess.pdf

[3] "For a number of well-known reasons, expanding the use of administrative data in the production of business statistics is something between a desirable goal and an inescapable necessity", in Costanzo, L, 'Use of Administrative Data and Use of Estimation Methods for Business Statistics in Europe: an Overview'. National Institute for Statistics Italy (ISTAT), Division of Statistical Registers, Administrative Data and Statistics on Public Administration, available at https://www.ine.pt.

[4] UK Strategy for Data Resources for Social and Economic Research 2013-2018, a five-year plan to inform and guide the development and related resources for social and economic research, e.g. "there is optimism that much better access to administrative data sources will yield major benefits" (p. 5), "Administrative data, routinely collected by public sector organisations and relating to individuals, have enormous research potential either to enhance existing surveys or census data, or in their own right" (p. 10), available at http://www.esrc.ac.uk/files/research/uk-strategy-for-data-resources-for-social-and-economic-research/.

the performance of firms. Our assessment takes into account firms' heterogeneity in terms of size, past performance and turnover per employee, and the self-selection of firms into this kind of publicly funded R&D activity.

Our findings show that participating in a publicly funded research project has on average a positive impact for employment and turnover growth. Employment grows faster both in the short and in the medium term, while turnover and turnover per employee growth effects are stronger in the medium term, suggesting a time lag between the research project and the ability of firms to commercially exploit the outcome of their R&D activity. Moreover, we find that the impact of publicly-funded research is stronger for manufacturing firms, in particular for high-tech manufacturing companies compared to low-tech manufacturing and other services firms. Although a larger share of projects involve large and more productive companies, our results also show that small and less productive firms experience the fastest growth after participating in publicly funded R&D projects, with particularly strong impacts on labour productivity (turnover per employee) growth.

The rest of the paper is organised as follows. Section 2 provides a comprehensive review of the main theoretical and empirical literature which links R&D support, innovation and firm performance. Section 3 presents the data used and discusses some preliminary statistics. Section 4 explains the variables used and the econometric methodology adopted in the empirical investigation. Section 5 presents and discusses the results of the econometric analysis, while Section 6 concludes summarising the key results and presenting some policy implications.

2. CONCEPTUAL FRAMEWORK

Public support for private R&D is generally justified in terms either of market failures linked to firms' difficulty in appropriating the returns from R&D, or for more strategic objectives linked to a desire to build capacity in specific sectors, technologies or localities. In either cases the objective is to incentivise increased levels of private sector R&D activity which, it is hoped, will in the longer term lead to increased innovation capabilities and improvements in business performance. Following this pivotal justification, two main relationships have been investigated by the previous literature: a "weak" link from public support to R&D and innovation, and a "strong" link from public support to business performance through innovation (Porter and Van de Linde 1995).

2.1 The rationale for public support to private R&D

The key rationale for public support to private R&D is the possible impact on knowledge creation which can provide the basis for subsequent innovation and value creation. The existing literature has identified four alternative mechanisms which may link public R&D support to firms' increased innovation activity and economic performance.

First, public R&D support will increase liquidity and financial slack in recipient companies which may help in over-coming risk aversion, a factor which may be particularly important in conditions of uncertainty (Palmer and Wiseman 1999). In fact, slack resources could increase the likelihood that a firm will undertake risky projects such as innovations (Zona, 2012). However, slack resources may also have negative effects, as managers are insulated from market realities, encouraging inertia or poor resource allocation towards highly risky projects (Nohria and Gulati, 1996). These opposite effects could suggest the potential existence of an inverted U-shape relationship between slack and innovation, where too little slack resources may hinder innovation, while too much may reduce firms' incentives to innovate, with the potential risk of over-subsidising innovation and increasing potential grant dependency (Kilponen and Santavirta, 2007).

Second, through cost-sharing, public support for private R&D reduces the required investment and de-risks private investment in R&D activities. Behavioural models of innovation suggest that firms' willingness to engage in innovation is positively related to anticipated post-innovation returns and negatively related to the perceived riskiness of the project (Calantone et al. 2010; Mechlin and Berg, 1980). The perceived riskiness of an innovation project will itself reflect the technological complexity of the project as well as commercial concerns about sales, profitability and potential competition (Keizer and Halman 2007; Roper, Du, and Love 2008; Cabrales et al. 2008). Technological innovation risks are associated primarily with the potential failure of development projects to achieve the desired technological or performance outcomes, the inability to develop a solution which is cost-effective to the manufacture/deliver (Astebro and Michela 2005), or issues around project development time (Menon, Chowdhury, and Lukas 2002; Von Stamm 2003).

Each of these issues may have implications for the subsequent market success or viability of an innovation. Market-related innovation risks have a commercial dimension linked directly to the demand for the innovation, but may also involve issues around rivalry or appropriability conditions. Astebro and Michela (2005), for example, emphasise demand instability as one of three main factors linked to reduced innovation survival in their analysis of 37 innovations supported by the Canadian Inventors Assistance Programme. Market rivalry and competitors' responses may also play a critical role in shaping market-related innovation risks. Rivals' new product announcements may reduce future returns (Fosfuri and Giarratana 2009), for example, while appropriability conditions may shape firms' ability to benefit from new innovations and therefore shape their market strategy (Leiponen and Byma 2009). The technological and market related elements of innovation risk are not independent, however, as Keizer and Halman (2007) suggest: "Radical innovation life cycles are longer, more unpredictable, have more stops and starts, are more context-dependent in that strategic considerations can accelerate, retard or terminate progress, and more often include cross-functional and or cross-unit teamwork. Incremental projects are more linear and predictable, with fewer resource uncertainties, including simpler collaboration relationships". In this context, public support may encourage firms to undertake projects with a higher risk-reward ratio, with the potential for a greater impact where rates of subsidy are higher. At the same time, there is a risk of negative selection bias if subsidy rates are high and this encourages firms to seek public support for their riskier projects.

Third, where there are market failures, public support for innovation may have market-making objectives to address particular social or economic challenges (Mazzucato, 2016). For example, there may be a particular role for public sector market-making where technologies are emergent and markets uncertain (Van Alphen et al. 2009), or where there are wider social benefits (e.g. to disadvantaged groups) from an innovation (Zehavi and Breznitz 2017).

Fourth, public R&D support can play an enabling or bridging role, helping firms to access otherwise unavailable new or pre-existing knowledge. Innovation vouchers, for example, incentivise firms to approach knowledge providers, something they may not have done without the voucher. At the same time vouchers incentivise knowledge providers to work with new partners who they might not have worked with otherwise (OECD 2010). Once partnerships are formed, subsidies may support individual or collaborative R&D activity which may lead to the creation of new knowledge, skills and capabilities. These, in turn, may lead to either rent-based, pure knowledge spillovers and then economic growth (Beugelsdijck and Cornet 2001).

2.2 From public R&D support to innovation and business performance

Following the economic theories which have identified the market failures that justify public support, a large body of literature has provided empirical evidence regarding the relationship between public R&D support, innovation and business performance. Particularly vast is the literature investigating the effectiveness of R&D subsidies and other public support strategies in promoting innovation and R&D investments, with considerable heterogeneity in terms of methodological approaches and empirical results. Zuniga-Vicente et al. (2014), reviewing more than 70 empirical studies on the relationship between subsidies and R&D investment, conclude that the large majority of studies on this topic find a complementary role of public subsidies, thus adding to private R&D investment. However, the authors stress how some critical issues related to this analysis have been largely neglected, such as firms R&D dynamics and composition, the source of R&D public funding (Czarnitzki and Lope-Bento, 2014) and other constraints faced by firms. In this vein, the survey by Becker (2015) concludes that, for instance, the additionality effect has been shown to be particularly prevalent for small firms, which are more likely to experience external financial constraints, and that these firms are more likely to start investing in R&D if they receive a subsidy. The survey also concludes that the more recent literature observes a shift away from earlier findings that public subsidies often crowd out private R&D to finding that subsidies typically stimulate private R&D, one reason likely being the availability of new econometric techniques that control for sample selection bias. In a more recent review of more than 50 micro-level studies published since 2000, Dimos and Pugh (2017) using a meta-regression analysis have investigated the effectiveness of R&D subsidies on either firms' R&D input or output. Despite the lack of conclusiveness of the evaluation literature, this study rejects any crowding-out effect of private investment by public subsidy, but also reveals no evidence of substantial additionality. In addition, the authors also stress the relevance of controlling for unobservable firm heterogeneity in order to properly estimate the effectiveness of R&D public support and reduce the bias related to omitted variables which could explain the participation of firms into support programs and thus influence the magnitude of the estimated effects (Greene, 2009; Dimos and Pugh, 2017).

Overall, while conceptual arguments are ambiguous, the balance of empirical evidence suggests a positive link between financial resources and innovation. In addition, the most recent literature has pointed out how several other factors might influence the effectiveness of public R&D support. For example, based on an analysis of Italian companies, Zona (2012) finds that financial slack resources in businesses offset risk-aversion and encourage investment in innovation especially through recessionary periods. Marlin and Geiger (2015) in their analysis of US manufacturing firms also emphasise, however, how firms can combine bundles of uncommitted resources to improve innovation outcomes. Becker et al. (2016) for instance using panel data on the UK and Spain have evaluated the effectiveness of regional, national and EU innovation support in promoting the extent of innovation activity and its market success. For both the UK and Spain, the authors find that national innovation support is associated with a higher probability of product or service innovation, and the degree of novelty of product or service innovations. Evidence for Korea suggests a weaker relationship, however, dependent on firms' size and internal capabilities (Lee, 2015). Moreover, several studies have focused their attention on the role played by uncommitted resources in setting up collaborative R&D projects between private and public organizations which may also allow firms to share risks with partners, but also raise additional issues around IP ownership and leakage.

However, the positive effects of public R&D support on private R&D investment and innovation do not necessarily mean that these public programs enhance productivity and thus eventually contribute to economic growth (Cin et al., 2017). In order to assess the existence of such relationship, a second stream of research has emerged, investigating the link between public R&D support, innovation input, output and firm performance.

The first papers in this field focused mostly on United States innovation and technology programs, providing mixed results of the impact on productivity and profitability (Lerner, 1999; Wallsten, 2000; Feldman and Kelley, 2003). More recently, the European Union Framework Program has attracted much attention, with several studies analysing the impact on both innovation output and economic performance (Bayona-Sáez and García-Marco, 2010; Czarnitzki and Lopes Bento, 2013; Czarnitzki and Lopes Bento, 2014). The range of these studies is broad and the results found are mixed. Some studies find that subsidy recipients achieve higher innovative productivity, and are more likely to improve their financial performance (Lerner, 1999; Gonzalez et al., 2005; Zhao and Ziedonis, 2014; Czarnitzki and Lopes Bento, 2014; Howell, 2017). In addition to the positive impact on R&D expenditure (Hottenrott and Lopes-Bento, 2014; Bedu and Vanderstocken, 2015), most of the literature has identified a positive role played by R&D public support on firms' investments (Von Ehrlich and Seidel, 2015), employment growth (Criscuolo et al., 2016), value added (Duch et al., 2009), and patent applications (Doh and Kim, 2014). Others instead conclude that public innovation grants do not improve significantly firms productivity, employment or the export performance of firms (Klette et al, 2000; Wallsten, 2000; Duguet, 2004; Gorg and Strobl, 2007; Martin, 2012; Karhunen and Huovari, 2015; De Blasio et al., 2015; Criscuolo et al., 2016).

For instance, Czarnitzki and Lopes-Bento (2013) have reviewed the value-for-money effect of a specific government-sponsored commercial R&D program in Flanders, considering how these effects could vary over time, according to the different sources of funding and the cumulative and sequential impact of different supported projects for each single firm. The authors find a positive impact of public support on the creation of new R&D jobs, with a stable effect over time regardless of the subsidies sources and the number of grants received. Criscuolo et al. (2016), following a regional analysis of the changes in the area-specific eligibility criteria for a major program of investment subsidies, find that areas eligible for public support create significantly more jobs. However, this effect seem to exist solely for small manufacturing firms, which experience a higher probability of entry and larger investment, despite no significant effect on total factor productivity. Similarly, another study by Cin et al. (2017) has recently investigated the effects of R&D promotion policy on the performance of firms in South Korea, with specific attention on SMEs. Controlling for counterfactual outcomes employing a difference-in-differences (DID) methodology, the authors find significant evidence of positive effects of the public R&D subsidy on both the R&D expenditure and the value added productivity of Korean manufacturing SMEs. However, Wang et al. (2017) using administrative data on applications to China's Innofund program, have first estimated which application are associated with higher chances of obtaining grants before evaluating the causal impact on firm performance using a regression discontinuity design. After controlling for selection bias, the authors find no evidence that receiving an innovation grant boosts survival, patenting, or venture funding.

Among the several reasons for such heterogeneity of results across the set of empirical studies, the most important are that the design and implementation of subsidy programs are heterogeneous across countries, regional contexts, industries, time periods and that researchers use different methods and units of analysis in their studies (Klette et al., 2000). In addition, another possible explanation behind the lack of cohesion among empirical findings is the limited theory available which models and predicts the types of effects resulting from the public R&D intervention on the performance of firms (Wang et al., 2017). Particularly relevant in this regard is the methodological approach followed by researchers and the ability to properly estimate the counterfactual associated with subsidy receipt (Jaffe, 2013). Since programs do not use random assignment to allocate grants, it is very difficult to isolate selection effects from the treatment effects. Previous research has used several approaches to overcome this problem, including identifying the potential outcome, estimating two-step selection models, comparing beneficiaries to a sample of applicants who did not receive grants and using structural approaches. Summarising, both selection and matching comparison are key methodological issues which have to be taken into account in order to properly evaluate the effectiveness of public support to private R&D.

Finally, a last strand of the policy evaluation literature considers instead the differences between public innovation policies aimed at helping individual private research versus subsidies which target collaborative research projects. These studies add to the substantial evidence from a range of countries on the benefits of collaborative innovation and the positive role of universities in helping firms to innovate successfully (Love, Roper, and Bryson 2011; Woerter and Roper 2010; Rantisi 2002; Petruzzelli 2011; Laursen and Salter 2006; Bellucci et al., 2016). The main benefits highlighted by this literature include fostering firms' innovativeness by internalising positive spillovers, sharing risks, accelerating or upgrading the quality of the innovations made, and signalling the quality of firms' innovation activities. However, theories on collaborative R&D projects indicate that alongside the benefits there might be significant drawbacks associated with research alliances, such as the costs to find suitable partners, coordinating and managing research networks, possible leakage of innovation and technologies, free-riding and opportunistic behaviours (Grimpe and Kaiser, 2010; Lokshin et al., 2011; Hottenrott and Lopes-Bento, 2016; Bellucci et al., 2016).

Also in this case, the vast empirical literature analysing the impact of subsidies for R&D collaboration on firms' economic performance has resulted in quite mixed results, generally agreeing on the existence of a positive relationship between the support of close-to-market R&D cooperation and economic performance (Aguiar and Gagnepain, 2017). For instance, Barajas et al. (2012) analysed the effects of international research joint ventures supported by the EU Framework Programme on Spanish firms' economic performance. Taking into account the selection process for the participation of firms into this type of cooperative projects, their empirical analysis confirms that supported R&D cooperation has a positive impact on the growth of intangible fixed assets, with indirect positive effects on the productivity of participating firms. More recently, Scandura (2016) focused on the R&D impacts of Engineering and Physical Sciences Research Council (EPSRC) grants awarded to university-industry collaborations in the UK, finding a positive and significant impact on the share of R&D employment two years after the end of projects. Similarly, Aguiar and Gagnepain (2017) have analysed the research joint ventures supported by the 5th EU Framework programme and their impact on companies' performance. Stressing that R&D collaborations are activities characterised by long-term objectives, their results suggest a strong long-term effects on the labour productivity of participants, growing by at least 44% four years after the beginning of the collaborative project. Bellucci et al. (2016) instead focus their attention on the effectiveness of regional R&D policies designed to support firms' individual projects or collaborative R&D ventures between firms and universities. Using a difference-in-differences approach the authors show that the supported individual projects are particularly successful in stimulating additional R&D investment and just partially firms' performance. On the contrary public support to firm-university collaboration seems to have weaker effects, mostly increasing R&D expenditure and employment growth. Differences in the results of these empirical studies might be related to the different frameworks of the supporting programmes, the types of partners involved and the focus of the collaborative projects, frequently differing between industry-oriented or knowledge-oriented projects (Hewitt-Dundas et al. 2017). For instance, different types of partners may shape project objectives and duration, with market based collaborations reducing project duration of all types of projects while collaborations with universities and research institutes only reducing the duration of complex products (Du et al. 2014).

3. DATA

3.1 The Gateway to Research Data

For our analysis we draw on funding and partnership data from the Gateway to Research (GtR) website[5] developed by Research Councils UK (RCUK) to provide information about all publicly funded research projects, including data from the Arts and Humanities Research Council (AHRC), the Biotechnology and Biological Sciences Research Council (BBSRC), the Economic and Social Research Council (ESRC), the Engineering and Physical Sciences Research Council (EPSRC), the Medical Research Council (MRC), the Natural Environment Research Council (NERC), the Science and Technology Facilities Council (STFC), Innovate UK and the National Centre for the Replacement, Refinement and Reduction of Animals in Research (NC3Rs). The Gateway to Research database provides information on all funded projects over the 2004 to 2016 period, reporting their topics and outcomes as well as the characteristics of the partners involved in each research project. This database includes information about approximately 34,000 organizations that have participated in publicly

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[5] We abstracted the data for this study between the 2nd and the 5th of January 2017 from the Gateway to Research website available at the following link: http://gtr.rcuk.ac.uk

funded innovation and R&D projects over this period, including details on the number and value of funded projects, the number and characteristics of partners by organization type and country, the total value of grants awarded per year, the research council source of the funding, and information about the projects leaders, their role and nationality. Financial support not included in GtR includes support which was provided by the Regional Development Agencies prior to 2010, EU Framework Programmes and support provided by agencies in the Devolved Territories as well as any contributions made by project partners. The GtR data also relates solely to the public funding contribution to each project, it does not provide any indication of the contribution by firms or other organisations.

The heterogeneity of the research councils included in this database reflects the diversity of modes of access to the science system in the UK and the diversity of the types of university-industry interaction. In fact, the projects supported differ widely across Councils, from grants from Innovate UK to support research in individual companies to collaborative research awards from the research councils which may involve numerous corporate and university partners in the UK and internationally. In addition, the focus of awards may also be very different, from purely responsive mode where research councils have an open call for high quality research ideas, to more strategic investments which seek projects around a particular theme or topic. Unfortunately, the database reports only the projects successfully funded by research councils, not allowing us to control for the selection and rationing process. This means that we can only observe a small proportion of those projects actually proposed and we are not able to evaluate what happened when a project was not supported.

Table 1 presents a preliminary breakdown of the total number and value of projects supported by UK Research Councils over the period 2004-2016 by funding source. Over 13 years the UK Research Councils have funded more than 70,000 research projects, allocating almost £32 billion. The largest funders are the Engineering and Physical Sciences Research Council (EPSRC) supporting 22% of total projects and allocating almost 30% of the overall funds available, followed by the Medical Research Council - funding only 10% of the total number of projects but accounting for more than 22% of the total value - and Innovate UK responsible for the support of almost 20% of all projects and allocating more than

15% of all resources.

Table 2 describes the distribution of the number and value of projects funded by UK Research Councils according to the type of participating organization and country of origin of participants. We categorized the almost 34,000 participating organisations in 11 different categories: private firms, universities, public research institutes and projects, private R&D centres, schools, hospitals, government authorities, research councils, charities, cultural organizations and others[6]. The largest group of organizations is private firms, with more than 18,500 firms participating in funded projects, followed by public research institutes (2,600), universities (2,100) and charities (2,100).

As shown in the first map in Figure 1, several foreign organizations around the world have participated in projects funded by the UK research councils, especially EU based organizations (almost 4,000) and US based organizations (more than 2,000). In the case of non-UK organizations, the largest category is private firms, with almost 4,000 foreign firms participating in projects funded by UK research councils, followed by public research institutes (1,820), foreign universities (1,571) and hospitals (almost 1,000). The second map in Figure 1 presents the distribution of participating private firms across foreign countries, highlighting a distribution of participating firms in a smaller number of foreign countries and with a particular concentration in the EU (particularly in Germany and France), the US and Japan. Figure 2 presents the geographical distribution of all UK organizations and firms who participated in projects supported by the UK research councils over the 2004-2016 period. Not surprisingly, it is possible to notice a high concentration of participants in the central part of England and around the main cities of the country, in particular around London, Bristol, Oxfordshire and Cambridgeshire, the Midlands, Merseyside, greater Manchester, the Tees Valley, Newcastle and the main cities in Scotland Edinburgh and Glasgow. (Note, however, that it is possible that in multi-site organisations R&D projects may be located across sites although the award data suggests a single address).

[6] We define as others academic journals, associations, funds, membership organizations and federations.

Thanks to the rich dataset provided by GtR we can also analyse the dynamic evolution of the funding awarded by research councils over the 2004-2016 period. Figure 3 reports in the first graph the total value of grants awarded every year by each Research Council, while focusing only on grants in which private firms participated in the following graph[7]. First, note that for the majority of Research Councils the data are available starting from 2006, while only for the Medical Research Council and Innovate UK the data start in 2004. Since 2007 the Engineering and Physical Science Research Council (EPSRC) has been the largest provider of R&D public funds, despite a rapid catch up by Innovate UK since 2012. The Medical Research Council holds a stable and relevant role in funding throughout the period, closely followed by the Biotechnology and Biological Sciences Research Council (BBSRC), while the remaining research councils awarded on average less than £ 200 million per year each. Focusing on grants in which private firms participated in the second graph the distribution is quite different. Innovate UK and the EPSRC are dominant here funding the largest proportion of projects in which firms participate, with a prominent role played by Innovate UK especially since 2012, with an overall investment of almost £500 million in 2015.

3.2 Firm-level data

In order to evaluate the "money to knowledge-knowledge to money" effect of grants awarded by UK research councils in which private firms have participated, we have matched the GtR data with micro-level data on the economic performance of firms from the ONS Business Structure Database (BSD) accessed through the UK Data Service, covering the whole population of business in the UK between 1997 and 2016. The annual BSD dataset is a live register of data based on the annual abstracts from the Inter-Departmental Business Register (IDBR) and collected by HM Revenue and Customs via VAT and Pay As You Earn (PAYE) records covering the population of firms operating in the UK. The BSD provides information on firms' age, ownership, turnover, employment, industrial classification at the SIC 4-digit level and postcode. We

[7] Here we aim to give an overall idea of the value of projects in which firms participated. Where projects were collaborative we divide the project value equally between the participants.

structured the longitudinal BSD data as a panel in order to analyse the dynamic impact of public funded R&D on the performance of participating firms, in particular in terms of employment, turnover and labour productivity (turnover per employee) growth. Using the CRN numbers provided in GtR data, or assigned manually by name using the Bureau Van Dijk ORBIS database, we have been able to match almost 10,000 UK firms who have participated in publicly funded research projects from the UK Research Councils with the BSD dataset, combining in this way information on the R&D grants awarded and firm-level characteristics.

4. METHODOLOGY

Although the descriptive evidence is useful, to understand the causal relationship between the award of grants and the performance of firms participating we take an econometric approach. Specifically, we are interested in comparing the differences before and after firms have participated in publicly funded research projects in comparison to other firms who haven't.

However, a significant hurdle in the identification of this causal relationship is the possibility of significant endogeneity. Participation in research projects is not an exogenous and randomized treatment but is very likely to be affected by endogenous factors influencing the decision and the self-selection of firms into this kind of programmes.

Hence, in order to properly estimate the causal effect of publicly funded research on the performance of firms we apply a difference-in-difference (DID) propensity score matching (PSM) technique at the firm-level (Lechner, 2002; Leuven and Sianesi, 2017). Our identification strategy is to compare the performance of firms before and after they participated in the publicly-funded projects and to compare the effects to a control group of firms that were not engaged in research supported by the UK research councils. By the construction of a valid control group based on the observable differences between participants and non-participants, our matching approach controls as best we can for any endogeneity bias. The final aim is to assess the average treatment effect on the treated (the ATT effect), in other words to estimate the difference of the outcome variable between observations which have been treated and similar ones which instead have not been treated, before and after the research project.

To compare the differences before and after the research project, we rescale the time periods in order to consider time t=0 as the time in which firms participate in their first publicly funded research project, or as the median year for firms who did not participate. Based on that we measure the average growth rate of the outcome variables y_{t+n}^{1} (employment, turnover and labour productivity measured as turnover over total employment; n denotes number of years after the project and superscript 1 indicates the start of the project) in the short (from year 0 to 2) and medium term (3-5) in comparison to the pre-treatment period at time t-1, in order to assess the effect of the publicly funded projects in the short and medium term.[8]

Since we are interested in identifying the differences in firms' performance after a firm participates in a research project, we can express the average treatment effect (τ_{ATT}) on the performance of a treated firm in terms of the difference between the average performance outcome in period *t+n* after the start of the project, $E(y_{t+n}^{1}|\, S_t = 1)$, and the counterfactual average performance outcome for the same group of firms, had they not participated, $E(y_{t+n}^{0}|\, S_t = 1)$:

$$\tau_{ATT} = E(y_{t+n}^{1} - y_{t+n}^{0}|\, S_t = 1) = E(y_{t+n}^{1}|\, S_t = 1) - E(y_{t+n}^{0}|\, S_t = 1)$$

where *S* denotes the two groups of firms, S=1 is the treated group participating in the project and S=0 is the untreated group. The fundamental problem is that only one of the two possible cases is observed for each firm, whether the firm has participated in publicly funded research projects or not, while the counterfactual for the same observation could not be observed.[9] Hence, we need to build a suitable control group by considering instead the effect of no treatment on the performance of similar firms which did not participate in a research project.

To build the control group we use a propensity score matching technique in order to select from the (very large) group of untreated observations suitable control

[8] As part of the matching procedure, after identifying a treated firm at t=0, we drop the subsequent observations of the same firm so that a firm cannot be matched with itself or be erroneously included in the control group after being treated.
[9] That is, we observe $E(y_{t+n}^{1}|\, S_t = 1)$ and $E(y_{t+n}^{0}|\, S_t = 0)$.

groups for which the distribution of observed characteristics are as close as possible to the distribution of treated observations before the start of the research project (Rosenbaum and Rubin, 1983; Heckman et al., 1997; Becker and Ichino, 2002). The first step is to estimate the probability that any firm participates in a publicly-funded research project, the so-called propensity score, based on a set of observable characteristics. We use a logit model to estimate the propensity score for all observations, using several covariates which may explain the probability of participation. First we include a set of firm-level variables such as employment and turnover levels, age, employment and productivity (turnover per employee) growth in the 2-years period before the projects have been awarded to control for any possible pre-treatment trend, group and foreign ownership dummies and whether firms are located in the same postcode district as a science park. In addition we include other control variables at the industry-region level to control for location and sector specific factors, such as the Ellison and Glaeser (1997) agglomeration index per region and industry, the regional R&D intensity, the region-industry competition level measured with the net entry-exit rate, region-industry employment and turnover per employee level, dummies for manufacturing high-tech and knowledge intensive services and finally year, region (LEP or NUTS 2-digit level) and industry (SIC 4-digit) dummies.[10]

The results of the propensity score estimation are reported in Table A1 in the appendix and the signs and significance of each estimator are consistent with the previous literature. Note that large and younger firms are more likely to participate in research projects funded by UK research councils, especially if they are part of a business group and are domestically owned. Firms located close to a science park and in more R&D intensive regions have a higher probability of treatment, especially if operating in knowledge-intensive services sectors. After estimating the probability of participating in a publicly funded research project, we

[10] Following the Eurostat classification, manufacturing high-tech firms have SIC codes (2003) equal to: (24) chemicals and pharmaceuticals; (29) machinery and engines; (30) computers and office machinery; (31) electrical machinery; (32) IT and communication equipment; (33) medical, precision and optical instruments; (34) motor vehicles; (35) transport equipment. Knowledge-intensive services (KIS) include the following sectors: (61) water transports; (62) air transports; (64) post and telecommunications; (65) financial intermediation; (66) insurance; (67) auxiliary activities to financial intermediation; (70) real estate; (71) renting of machinery and equipment; (72) computer related activities; (73) research and development; (74) other business activities; (80) education; (85) health and social work; (92) recreational, cultural and sporting activities.

proceed by matching the untreated and treated observations according to their estimated propensity score, matching untreated observations which have estimated probabilities which are as close as possible to those of the treated firms. First, we impose a common support condition, dropping the treated and untreated observations whose propensity score are larger or smaller than the maximum or minimum of the other category. Secondly, we apply a nearest neighbour matching technique with a strict calliper bandwidth of 0.5, matching each treated observation only with the closest untreated observations within a 0.5 range in the propensity score. In addition, we force the matching to be just within firms located in the same region at the LEP or NUTS 2–digit level and operating within the same sector at the SIC 4-digit level, in order to compare treated observations only with other untreated firms part of the same region and sector, to reflect as well the industrial heterogeneity in the number of firms and the value of grants, with similar characteristics and with the closest probability of participating in research projects as possible. As a robustness check in Table A3 in the appendix we apply as well a Kernel matching technique with a strict bandwidth of 0.05, using a kernel-weighted distribution which down-weights the contribution to the outcome of non-treated individuals which are further from the propensity score of treated observation within a certain range (i.e. the bandwidth). Finally, we have clustered the standard errors following the Abadie and Imbens (2011) methodology for the nearest-neighbour matching procedure, while standard errors have been bootstrapped with 500 repetitions for heteroscedasticity consistency when using the kernel matching algorithm, in order to take into account the additional source of variability introduced by the estimation of the propensity score (Heckman et al. 1997).

After estimating the propensity score, dropping the outliers and keeping only firms in the common support our final sample contains almost 6,000 UK firms who participated in R&D projects from UK research councils and their related controls. Table A2 in the appendix reports the results of the tests which verify the consistency of the construction of the control group and the overall quality of the matching procedure. To check the propensity score balancing we report the mean differences across treated and control group for the set of variables used to estimate the propensity score before and after the matching took place. It is possible to notice that even if differences between treated and untreated observations are expected before the matching, these differences are significantly reduced after the matching has taken place, comparing in this way only closely comparable groups of treated and untreated firms. Note that the bias after the matching for all covariates is reduced below the 25% critical threshold, delivering a consistent and balanced matching, indicating that there are no systematic differences in the observable characteristics between treated and untreated firms included in the control group and that the matching procedure satisfies the balancing property and that the conditional independence assumption is not violated [11] (Rubin, 1977; Rosenbaum and Rubin, 1985; Caliendo and Kopeinig, 2008). Figure A1 confirms graphically the quality of the matching, showing that the probability of participating in publicly-funded research projects is balanced between treated and control groups, with a remarkably similar density distribution after the matching has taken place.

5. EMPIRICAL RESULTS AND DISCUSSION

To evaluate the heterogeneous impact of publicly-funded research on participating firms' performance, we implement the matching methodology, disentangling the effect for different groups of treated and untreated firms. After analysing the impact for the whole sample of firms, we differentiate between manufacturing and services firms[12], looking at the different impact for high-tech versus low-tech manufacturing firms and knowledge intensive service (KIS) firms versus non-KIS companies. [13] Table A3 in the appendix reports some basic summary statistics about the treated firms, i.e. those firms that participated in projects, included in each of the different groups of interest. Note that most of the treated firms operate in the knowledge-intensive services industries (KIS). These firms tend to be part of more publicly-funded projects than the average treated firm, with a higher grant-intensity (ratio of total grant value to total turnover) and a larger number of partners. KIS firms in addition are on average younger than the

[11] This assumption states that y^1_{t+n} and y^0_{t+n}, respectively, are statistically independent for firms with the same set of exogenous characteristics.
[12] Manufacturing sectors includes all industries with a SIC (2003) code between 15 and 37. Services sector includes all industries with a SIC (2003) code from 40 to 95.
[13] As a robustness check, the second panel in Table 4 focus only on the post-2008 period in order to isolate any impact of learning-effects and to avoid the estimation of effects related to the award of research grants received before 2004 and thus not observed in our data.

other treated firms, and are generally smaller and less productive than both non-KIS firms and other treated manufacturing firms.

Table 3 reports the main set of results of the evaluation of the impact of the participation in publicly-funded research projects on firms' performance. Panel 1 including all firms in our sample shows that participating in projects funded by UK research councils has on average a positive impact in particular for employment and turnover growth, both in the short and in the medium term. As a matter of fact, employment grows on average by 5.8% in the 3 years following the award, while by almost 22.5% in the medium term. Turnover as well increases in the short-run by almost 6% in relation to non-treated firms after the award, peaking in the medium-term with a 28% faster growth relative to non-treated firms. The effect on productivity (turnover per employee) growth instead is not as significant, registering a positive and statistically significant growth by almost 6.2% only in the medium term in relation to untreated companies. These findings may relate to the time lag between the start of projects and a significant improvement of firms' performance. The time lag might be caused by the necessity of long periods of time in order to develop new R&D activities and to exploit commercially the results of new research and innovations funded thanks to the UK research councils' support, as suggested by the previous literature (Barajas et al., 2012; NESTA, 2012; Dimos and Pugh, 2016). These results for the entire sample of firms are consistent with our additional tests in panel 2, where we focus our analysis only on the post-2008 period, as well as our robustness check in Table A4 in the appendix when using the kernel matching technique instead of the nearest-neighbour method.

Panels 3-8 report the results of the evaluation of the impact of participating in publicly-funded research projects on different sub-samples of firms, comparing manufacturing and services sectors, manufacturing high-tech versus low-tech firms, and finally comparing knowledge-intensive and non-KIS firms. The impact on the growth of recipients is stronger for manufacturing firms, increasing employment by 24% after 6 years, turnover by more than 30% and improving labour productivity (turnover per employee) both in the short and medium term by almost 8%. Also, the magnitude of the ATT effect is larger for firms operating in high-tech manufacturing sectors, compared with low-tech firms, despite a larger and significant positive growth for the labour productivity of low-tech firms, which are able to catch up more quickly in terms of productivity (turnover per employee) thanks to the support of UK research councils. Finally, involvement of private companies in R&D supported by UK research councils seems to be more beneficial in terms of employment and turnover growth for knowledge-intensive firms rather than other companies in the services industry, registering a positive and significant effect both in the short and medium term, with a slightly reversed picture for turnover growth. Labour productivity (turnover per employee) does not seem to be affected in the service industry, regardless of the knowledge intensity of firms.

By matching the GtR data with the BSD database we are also able to analyse the impact of engagement in research supported by the UK research councils on the performance of firms across UK regions. The maps in Figure 4 show the geographical distribution of the statistically significant effects on the medium-term employment, turnover and productivity (turnover per employee) growth across NUTS 1 regions. First, we note a large positive impact on the employment growth of project participants located in the Greater London area (+31%), in the South-East (+25%) and North-West (+25%) regions. In terms of turnover growth, the regions where the impact of participation is stronger are Scotland (+29%), Yorkshire (+31%) and again Greater London (+35%), highlighting a heterogeneous distribution of the positive impact of research and innovation grants across the whole country. Analysing the difference between employment and turnover growth across regions, it is possible to identify very few regions where the labour productivity (turnover per employee) growth has been statistically different for participants in innovation grants compared to non-treated firms.

As suggested by the previous literature on this research field, the impact of public R&D support on firms' performance could diverge widely from firm to firm even within the same industry or region due to the heterogeneity of firms in terms of scale, capital-intensity, productivity, employees skills and managerial strategies (Czarnitzki and Lopes-Bento, 2013; Dimos and Pugh, 2016; Bellucci et al., 2016; Cin et al., 2017). For these reasons, in Table 4 we evaluate the impact of research and innovation grants on the performance of participants across the size and productivity (turnover per employee) distribution of treated and untreated firms.[14] It is evident from both panels how smaller and least productive participants experience the largest performance growth in relation to their untreated counterparts. More specifically, the impact seems to be particularly large for the least productive companies in our sample, which after 6 years since the start of the award register an employment growth 23% faster than untreated firms, an increase in turnover by more than 50% and catching up quickly in terms of labour productivity (turnover per employee) with a leap forward by more than 22% on average in 6 years time. The relationship between R&D public support and firms performance seems to be negatively related with the distribution of firms' scale and productivity (turnover per employee), since we find a decreasing marginal effect as firms size and productivity (turnover per employee) increases and only tiny marginal differences in employment and turnover growth between treated and untreated firms in the top quartiles of the scale and productivity (turnover per employee) distributions.

Finally, following the preliminary evidence shown in Figure 3, we focus our attention on the research grants awarded by the two main UK funders responsible for the largest part of grants involving private firms, Innovate UK and the Engineering and Physical Science Research Council (EPSRC). Table 5 distinguishes the evaluation analysis between firms involved in projects funded by the EPSRC, Innovate UK and all the remaining UK research councils. Again, it is possible to notice that most companies have received support from Innovate UK, more than 4,000. EPSRC-supported activities have involved about 900 of the firms in this sample, while the remaining research councils together have funded grants involving nearly 560 firms. As expected, Innovate UK leads the R&D public support to private firms, due to its strong business focus on firms' growth, by working with companies to de-risk, enable and support innovation and the commercialization of R&D outputs. However, firms involved in projects funded by EPSRC seem to benefit much more in terms of employment and turnover growth, increasing their scale by 27% and their turnover by more than

[14] In terms of scale, we grouped firms according to their initial level of employment at time *t-1*, categorizing firms into micro (with 10 or less employees), small (between 10 and 50 employees), medium (between 50 and 250 employees) and large enterprises (more than 250 employees). In terms of productivity we grouped firms in four different quartiles according to the distribution of firms' labour productivity (turnover per employee) at time *t-1*.

30% in respect to comparable non-treated firms six years after the start of the project. Also firms who received R&D public support by Innovate UK experience a better economic performance than their untreated counterparts, but relatively smaller than firms participating in EPSRC supported research with an employment growth of 21% and a turnover growth of 23% in the medium term. In addition, firms involved in EPSRC funded projects register a positive labour productivity (turnover per employee) growth as well in the short-term by 2.3%, with turnover growing faster than employment. The relatively few firms involved in research projects funded by the other research councils also exhibit strong growth in terms of employment - by almost 30% in the medium term – but turnover and productivity growth effects are weaker.

6. CONCLUSIONS

In the last decade UK Research Councils and Innovate UK have supported research projects averaging more than £3bn pa, an investment which is set to increase by £2bn in 2020. To date, assessments of the impact of this public investment have been partial and largely case-based, often relying on limited information of innovation surveys or focused on specific industries, resulting in quite mixed results. In this study we have analysed the comprehensive effect of public support to innovation, assessing the impact of engaging with publicly-funded research grants on the performance of UK firms.

Using data on funding and partnerships from Gateway to Research on all funded projects by the UK Research Councils and Innovate UK over the 2004 to 2016 period and business performance data from the Business Structures Database we have applied a difference-in-differences propensity score matching technique to evaluate the performance of UK firms who participated in publicly-funded research grants in respect to a matched comparator group of firms which received no support. Our analysis suggests five main conclusions. First, firms involved in projects funded by UK research councils grew their turnover and employment 5.8-6.0 per cent faster in the three years after the award, and 22.5-28.0 per cent faster in the six years after the award, than similar firms which did not participate. Second, the impact of participation is larger for firms in high-tech manufacturing and knowledge intensive services. Third, we identify significant differences in the regional impacts of public support for R&D, linked inevitably to concentrations of different industry types. Fourth, we find evidence that the impact of participation is larger for small firms and those with lower starting productivity (turnover per employee). Growth impacts on firms in the top quartile of the productivity (turnover per employee) distribution are small. Fifth, support relevant to businesses is provided largely by EPSRC and Innovate UK. Participation in projects funded by both organisations increases both employment and turnover growth in the short and medium terms with only marginal differences in their impact.

Overall, our analysis shows that the public support by UK research councils for research and innovation has a strong positive impact on participating firms' growth in the short and medium term. Long term effects are also likely to be significant but are harder to assess using our data. Our results echo those of other studies which have suggested – albeit on the basis of a more partial assessment – the value of public support for private R&D and innovation. In general terms this provides positive evidence for new investment in initiatives such as the Industrial Strategy Challenge Fund, particularly where this extends the number of firms which are able to participate in R&D projects.

Our analysis also provides some guidelines for targeting future support. Perhaps two results are key here. First, our analysis suggests that impacts are largest in high-tech and knowledge intensive sectors. Targeting firms in these sectors therefore seems sensible. Second, our analysis suggests that growth impacts are greatest in smaller firms and in those with lower productivity (turnover per employee), and suggests that growth effects in high productivity firms are small. This result suggests some trade-offs. Maximising growth impacts would suggest targeting support on smaller less productive firms, while maximising the impact on knowledge creation and new-to-market innovation would suggest targeting leading-edge, higher productivity businesses. Here, however, additionality in terms of growth may be more limited. One other interpretation of our results, which may have implications for policy targeting, is also relevant here. If high productivity firms in the UK are benefitting from public support for R&D and then generating growth elsewhere, not in the UK, this would not be picked up in our analysis. If this the case, targeting support on higher productivity (turnover per employee) firms with a requirement for UK exploitation may be a possible route forwards.

Our analysis comes with the usual caveats. First, data limitations mean that we measure economic impacts using turnover and employment data rather than value added per worker or hour worked. Second, we are only looking here at the direct effects of public support on participating companies. Much of the rationale for public support for private R&D and innovation relies not on these direct effects but on related spillovers. These we plan to explore in a further study, looking at local and industry effects on both innovation and growth. This hopefully will add to our understanding of both the spillover effects from publicly funded research and effects such as local clustering and agglomeration. Third, although the GtR data includes all public support provided by the Research Councils across the UK it does not include all public support for R&D and innovation. Other support is provided by agencies in the devolved territories in particular and it would be good to include this in any future assessment. Fourth, our analysis is solely UK-based and comparisons with other economies would be helpful. Fifth, we cannot from our data identify the mechanisms through which public support for science is impacting growth. This could be a knowledge creation effect but may also involve significant elements of cost-reduction, financial liquidity and risk reduction. Sixth, it is worth noting that due to data matching difficulties and the timing of some grant awards in 2015 and 2016 we are only able to look at growth effects on around two-thirds of assisted firms. Finally, it is worth noting that the GtR data contains a wealth of data which we have not exploited here, particularly around the characteristics and location of firms' research partners. Do firms working with networks with an international dimension derive greater growth benefits? More analysis is needed to address this type of question.

Table 1: Breakdown of the total number and value of projects supported by UK Research Councils over the period 2004-2016 by funding source.

	number	*share*	*Value (£m)*	*share*
Tot. Projects	70, 178	100.0%	31,811	100.0%
AHRC	5,585	8.0%	742	2.3%
BBSRC	11,208	16.0%	3,750	11.8%
EPSRC	15,528	22.1%	9,270	29.1%
ESRC	5,675	8.1%	1,930	6.1%
Innovate UK	13,870	19.8%	4,920	15.5%
MRC	7,250	10.3%	7,190	22.6%
NC3Rs	248	0.4%	49	0.2%
NERC	6,963	9.9%	2,430	7.6%
STFC	3,851	5.5%	1,530	4.8%

Notes: Statistics based on Gateway to research (GtR) data for the period 2004-2016. Value reported in £m. AHRC - Arts and Humanities Research Council; BBSRC - Biotechnology and Biological Sciences Research Council; ESRC - Economic and Social Research Council; EPSRC - Engineering and Physical Sciences Research Council; MRC - Medical Research Council; NERC - Natural Environment Research Council; STFC - Science and Technology Facilities Council; NC3Rs - National Centre for the Replacement, Refinement and Reduction of Animals in Research.

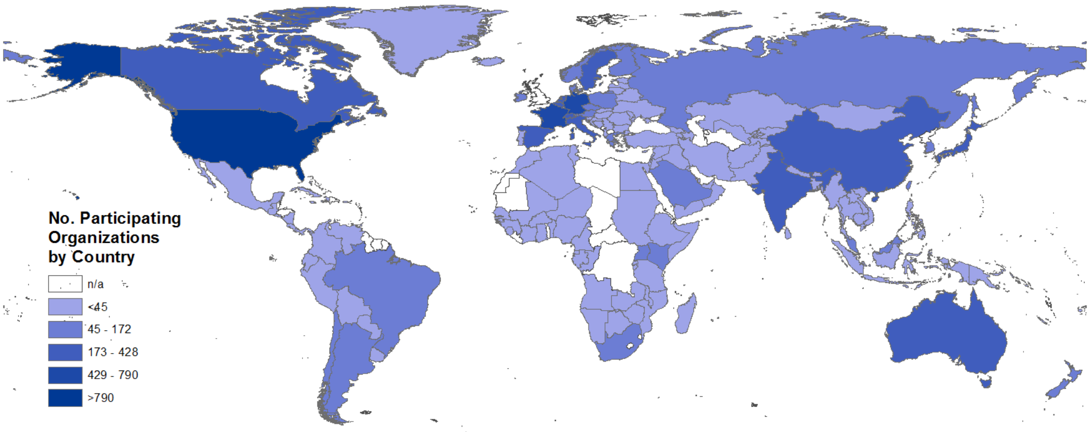
Table 2: Distribution of the number and average value of projects funded by UK Research Councils by organization type and country of origin of participants.

	UK	Non-UK	UK	Non-UK
	Firms		**Government**	
No. Organizations	14,854	3,679	747	561
Av. No. Partners	10.79	39.49	18.38	30.29
Av. Grant Value	98,104	93,464	77,205	70,420
Av. No. Projects	2.40	2.37	6.14	3.50
	Universities		**Research Councils**	
No. Organizations	543	1571	36	47
Av. No. Partners	13.33	31.75	24.09	15.76
Av. Grant Value	97,446	62,790	118,609	78,434
Av. No. Projects	109.77	9.17	63.97	5.30
	Public R&D Institutes		**Charities**	
No. Organizations	847	1,820	1,680	462
Av. No. Partners	18.26	42.14	23.75	43.20
Av. Grant Value	179,220	78,137	114,484	67,365
Av. No. Projects	9.00	3.32	2.84	1.78
	Private R&D Centres		**Cultural Org.**	
No. Organizations	68	97	490	226
Av. No. Partners	21.29	29.60	15.34	16.94
Av. Grant Value	97,632	74,695	32,315	42,478
Av. No. Projects	18.40	5.26	2.64	1.42
	Schools		**Others**	
No. Organizations	256	174	785	314
Av. No. Partners	15.22	23.68	20.12	28.53
Av. Grant Value	123,422	56,130	165,318	78,335
Av. No. Projects	40.09	3.99	2.56	2.83
	Hospitals			
No. Organizations	423	995		
Av. No. Partners	133.43	371.05		
Av. Grant Value	93,292	60,072		
Av. No. Projects	4.14	1.81		

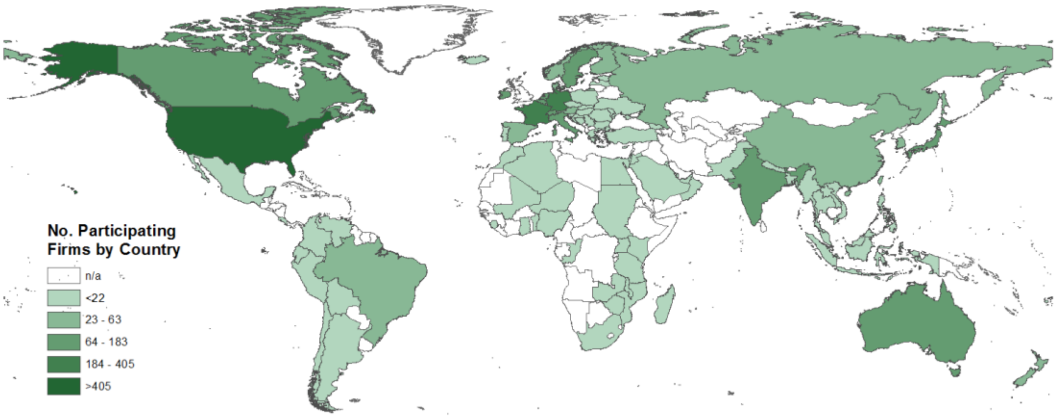
Notes: Statistics based on Gateway to research (GtR) data for the period 2004-2016 for UK and non-UK based organizations. Numbers reported are: average number of partners for each organization type; average grant value (£); average number of projects per organization. Where projects are collaborative, project value is divided equally between participating organisations.

Figure 1: Distribution of organizations and firms participating by country of origin.

a. Total number of organizations participating by country outside of the UK

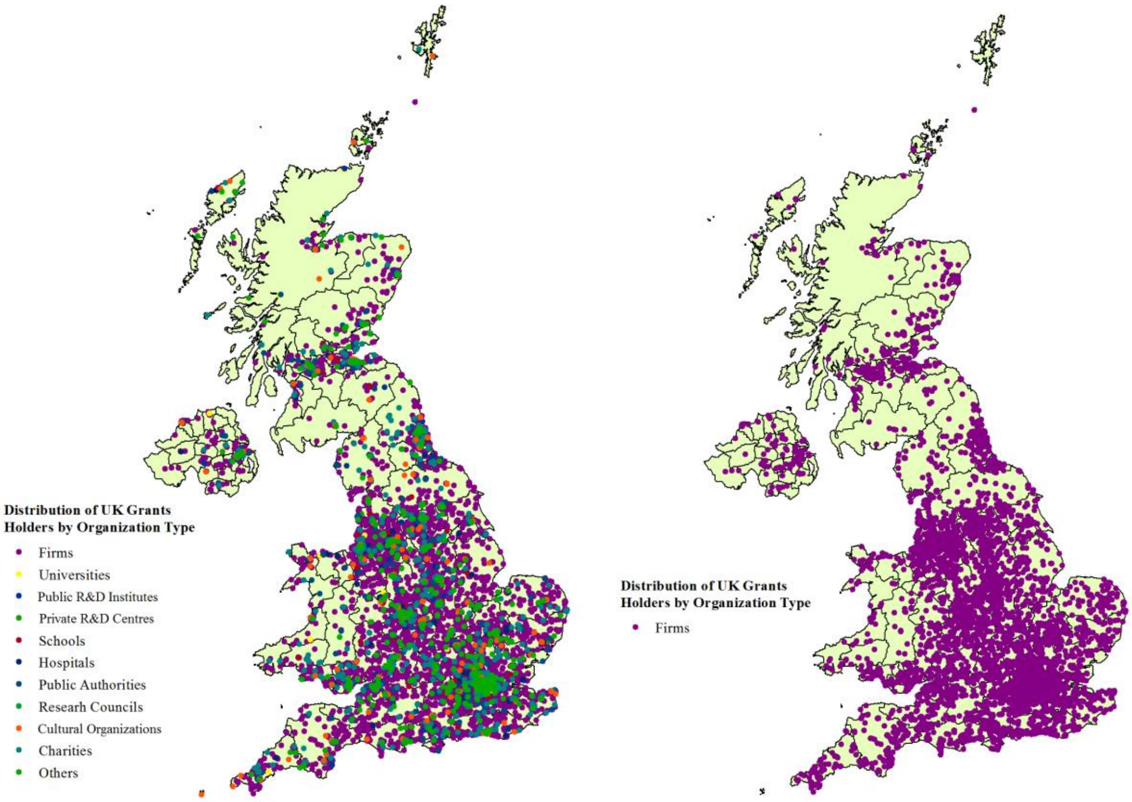


b. Total number of private firms participating by country outside of the UK



Notes: Statistics based on Gateway to research (GtR) data for the period 2004-2016 for non-UK based organizations.

Figure 2: Spatial distribution of organizations and firms participating

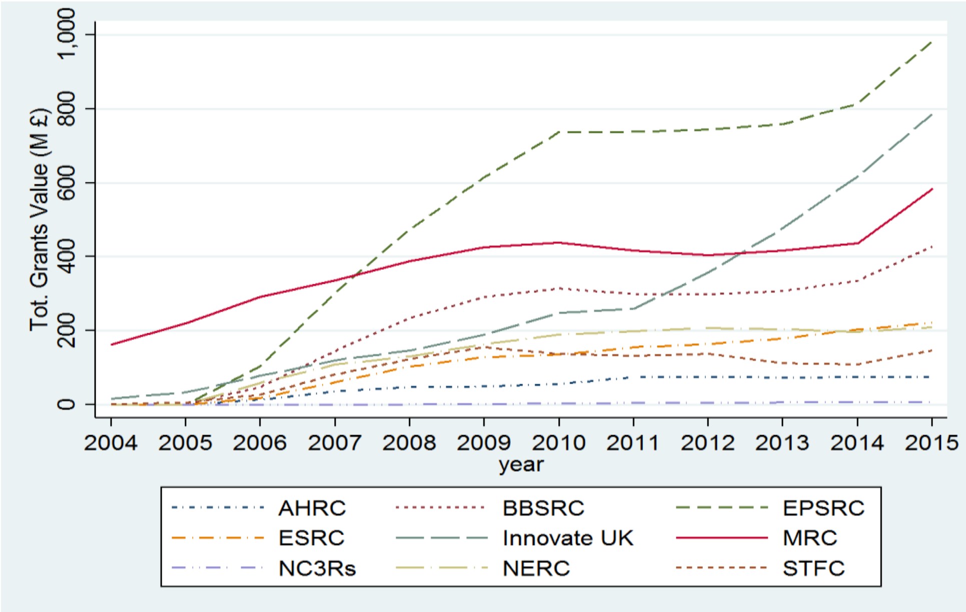


across the UK.

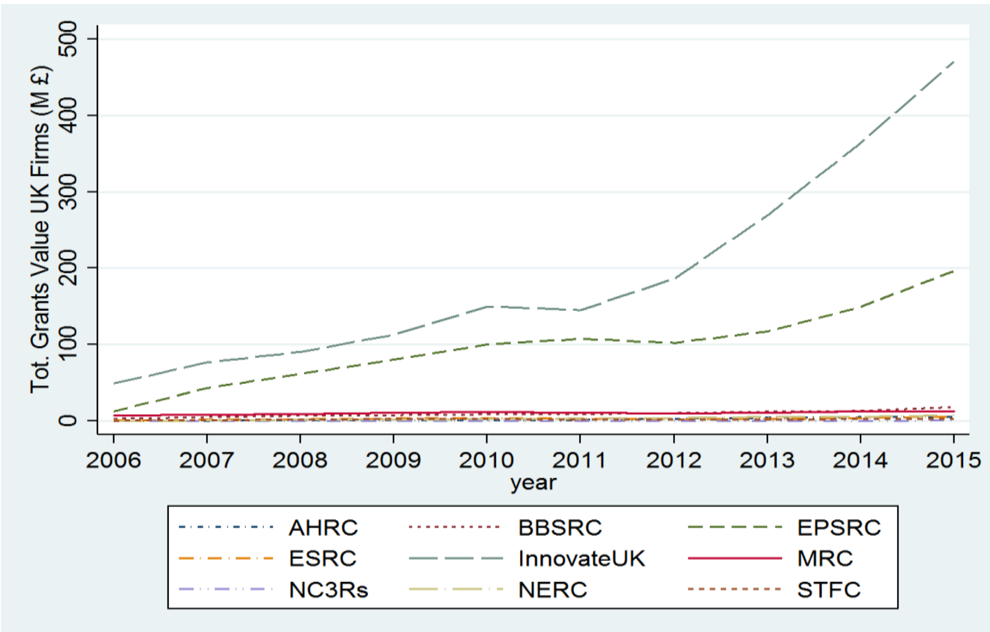
Notes: Statistics based on Gateway to research (GtR) data for the period 2004-2016 for UK based organizations. Spatial distribution based on the postcode of each organization.

Figure 3: Total project value per Research Council and year – all organizations and private firms only

a. **Total value of projects**



b. **Indicative value of projects with firm participants**



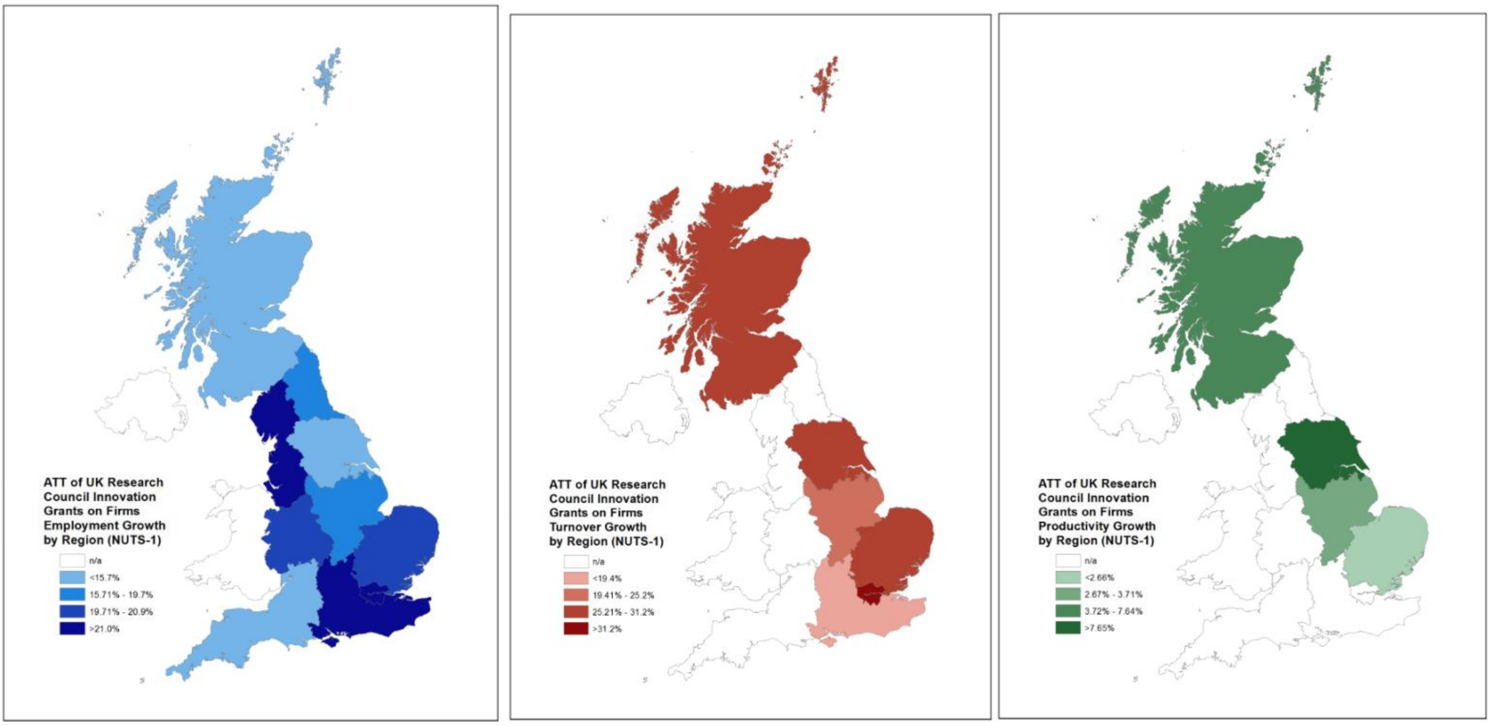
Notes: Statistics based on Gateway to research (GtR) data for the period 2004-2016. Project value reported in millions of pounds. Where projects are collaborative, project value is divided equally between participating organisations.

Table 3: Impact of participation in publicly-funded research on UK firms' performance – ATT effects with nearest-neighbour matching technique.

		1. All Firms		2. All Firms (post2008)		3. Manufacturing		4. Services	
		ST	MT	ST	MT	ST	MT	ST	MT
Employment	ATT	0.058***	0.225***	0.064***	0.211***	0.077***	0.242***	0.065***	0.235***
	s.e.	(0.008)	(0.018)	(0.008)	(0.020)	(0.014)	(0.034)	(0.010)	(0.021)
Turnover	ATT	0.064**	0.279***	0.071***	0.242***	0.135***	0.331***	0.054*	0.260***
	s.e.	(0.017)	(0.034)	(0.017)	(0.037)	(0.026)	(0.055)	(0.021)	(0.041)
Lab. Productivity	ATT	0.020	0.062**	0.013	0.029	0.041*	0.078**	0.012	0.055
	s.e.	(0.016)	(0.027)	(0.017)	(0.032)	(0.023)	(0.036)	(0.021)	(0.036)
Untreated		2,969,032	1,356,914	2,358,352	912,893	112,984	63,941	2,856,048	1,292,973
Treated		5,657	3,665	4,395	2,429	1,665	1,166	3,981	2,491
		5. Manuf. HT		**6. Manuf. LT**		**7. KIS**		**8. Non-KIS**	
		ST	MT	ST	MT	ST	MT	ST	MT
Employment	ATT	0.092***	0.275***	0.076***	0.238***	0.069***	0.243***	0.037	0.179***
	s.e.	(0.022)	(0.048)	(0.015)	(0.035)	(0.012)	(0.025)	(0.020)	(0.041)
Turnover	ATT	0.162***	0.398***	0.130***	0.342***	0.059*	0.247***	0.088*	0.258***
	s.e.	(0.043)	(0.081)	(0.029)	(0.057)	(0.026)	(0.051)	(0.033)	(0.071)
Lab. Productivity	ATT	0.061*	0.064	0.049*	0.082**	0.006	0.076	0.028	-0.003
	s.e.	(0.033)	(0.051)	(0.023)	(0.037)	(0.028)	(0.047)	(0.028)	(0.052)
Untreated		26,038	16,048	68,168	37,439	2,411,136	1,076,811	444,912	216,162
Treated		922	676	1,559	1,100	2,882	1,816	1,090	667

Notes: Estimation based on Gateway to Research (GtR) and the Business Structure Database (BSD) for the period 2004-2016 for UK based private firms. ATT effect estimated using a difference-in-differences technique with propensity score nearest-neighbour matching procedure. Abadie and Imbens (2011) standard errors (s.e.) reported in parentheses. *** p<0.01, ** p<0.05, * p<0.1. The number of firms included in the treated and control groups is reported. Labour productivity is proxied by the natural logarithm of turnover per employee. Manufacturing industry includes all SIC (2003) sectors between 15 and 36, service industry from sector 37 to 95. Following the Eurostat definition, manufacturing high-tech firms have SIC codes (2003) equal to: (24) chemicals and pharmaceuticals; (29) machinery and engines; (30) computers and office machinery; (31) electrical machinery; (32) IT and communication equipment; (33) medical, precision and optical instruments; (34) motor vehicles; (35) transport equipment. Knowledge-intensive services (KIS) include the following sectors: (61) water transports; (62) air transports; (64) post and telecommunications; (65) financial intermediation; (66) insurance; (67) auxiliary activities to financial intermediation; (70) real estate; (71) renting of machinery and equipment; (72) computer related activities; (73) research and development; (74) other business activities; (80) education; (85) health and social work; (92) recreational, cultural and sporting activities. Short-term includes years from time t to t+2, medium-term goes from time t+3 to t+5.

Figure 4: Geographical distribution of the statistically significant effects on the medium-term employment, turnover and productivity (turnover per employee) growth across NUTS 1-digit regions.



Notes: Estimation based on Gateway to Research (GtR) and the Business Structure Database (BSD) for the period 2004-2016 for UK based private firms. ATT effects estimated at the regional level (NUTS 1-digit level) using a difference-in-differences technique with propensity score nearest-neighbour matching procedure for the medium-term (3-5) growth of employment, turnover and labour productivity (turnover per employee).

Table 4: Impact of participation in innovation grants on performance across the size and productivity (turnover per employee) distribution of treated and untreated firms.

		Scale Distribution				Productivity Distribution			
		Micro	*Small*	*Medium*	*Large*	*1st*	*2nd*	*3rd*	*4th*
Employment	*ST*	0.099***	0.048***	-0.008	0.008	0.071***	0.061***	0.028	0.042***
		(0.010)	(0.015)	(0.023)	(0.028)	(0.018)	(0.016)	(0.018)	(0.013)
	MT	0.296***	0.254***	0.203***	0.144**	0.231***	0.152***	0.163***	0.218***
		(0.024)	(0.033)	(0.049)	(0.052)	(0.039)	(0.036)	(0.041)	(0.029)
Turnover	*ST*	0.109***	0.044	0.047	0.067*	0.130**	0.070**	0.022	0.042
		(0.026)	(0.034)	(0.038)	(0.043)	(0.049)	(0.030)	(0.029)	(0.025)
	MT	0.340***	0.314***	0.292***	0.108*	0.529***	0.200***	0.074	0.175***
		(0.053)	(0.063)	(0.077)	(0.075)	(0.089)	(0.062)	(0.065)	(0.047)
Lab.Productivity	*ST*	-0.011	-0.009	0.042	0.036	0.032	-0.009	-0.011	-0.009
		(0.024)	(0.027)	(0.032)	(0.038)	(0.040)	(0.026)	(0.027)	(0.021)
	MT	0.001	0.015	0.037	-0.039	0.225***	0.006	-0.092	-0.060
		(0.043)	(0.047)	(0.050)	(0.054)	(0.065)	(0.044)	(0.046)	(0.036)
	Control	2,721,152	199,317	40,236	8,327	844,211	722,413	623,597	778,811
	Treated	2,265	1,497	994	903	1,312	1,021	954	2,372

Notes: Estimation based on Gateway to Research (GtR) and the Business Structure Database (BSD) for the period 2004-2016 for UK based private firms. ATT effect estimated using a difference-in-differences technique with propensity score nearest-neighbour matching procedure. Abadie and Imbens (2011) standard errors (s.e.) reported in parentheses. *** p<0.01, ** p<0.05, * p<0.1. The number of firms included in the treated and control groups is reported. Labour productivity measured proxied as the natural logarithm of turnover per employee. Micro (with 10 or less employees), small (between 10 and 50 employees), medium (between 50 and 250 employees) and large enterprises (more than 250 employees). Firms grouped in four different quartiles according to the distribution of firms' labour productivity (turnover per employee) at time t-1. Short-term includes years from time t to t+2, medium-term goes from time t+3 to t+5.

Table 5: Impact of participation in publicly-funded projects awarded by EPSRC, Innovate UK and all the remaining UK research councils– ATT effects with nearest-neighbour matching technique.

	EPSRC			Innovate UK			Other RCs		
	Employment	Turnover	Productivity	Employment	Turnover	Productivity	Employment	Turnover	Productivity
ST	0.086***	0.141***	0.023**	0.057***	0.056***	-0.014	0.026	0.017	-0.003
	(0.021)	(0.044)	(0.011)	(0.009)	(0.019)	(0.016)	(0.026)	(0.053)	(0.043)
MT	0.271***	0.314***	-0.024	0.214***	0.232***	-0.017	0.307***	0.328	-0.026
	(0.043)	(0.081)	(0.058)	(0.021)	(0.038)	(0.028)	(0.051)	(0.201)	(0.070)
Control	2,969,032	2,969,032	2,969,032	2,969,032	2,969,032	2,969,032	2,969,032	2,969,032	2,969,032
Treated	914	914	914	4,032	4,032	4,032	561	561	561

Notes: Estimation based on Gateway to Research (GtR) and the Business Structure Database (BSD) for the period 2004-2016 for UK based private firms. ATT effect estimated using a difference-in-differences technique with propensity score nearest-neighbour matching procedure. Abadie and Imbens (2011) standard errors (s.e.) reported in parentheses. *** p<0.01, ** p<0.05, * p<0.1. The number of firms included in the treated and control groups is reported. Labour productivity is measured as the natural logarithm of turnover per employee. EPSRC - Engineering and Physical Sciences Research Council; Other RCs category includes AHRC, BBSRC, ESRC, MRC, NERC, STFC and NC3Rs. Short-term includes years from time t to t+2, medium-term goes from time t+3 to t+5.

APPENDIX

Table A1: Propensity score estimation using a logit model.

	Prob. Research Grant	
	Coeff.	*s.e.*
Employment	0.866***	(0.010)
Labour Productivity	0.004	(0.015)
Age	-0.317***	(0.024)
Pre-Employment Growth	0.133**	(0.056)
Pre-Productivity Growth	0.065*	(0.037)
Group	0.469***	(0.038)
Foreign Ownership	-0.409***	(0.050)
Science Park District	0.567***	(0.039)
Agglomeration Index	1.213	(1.998)
Regional R&D Intensity	0.037***	(0.008)
Competition Index	0.752**	(0.372)
Region-Industry Productivity	0.006	(0.054)
Region-Industry Employment	-0.336***	(0.027)
High-Tech Manufacturing	-0.417	(0.397)
KIS	0.441***	(0.150)
Observations	3,003,915	

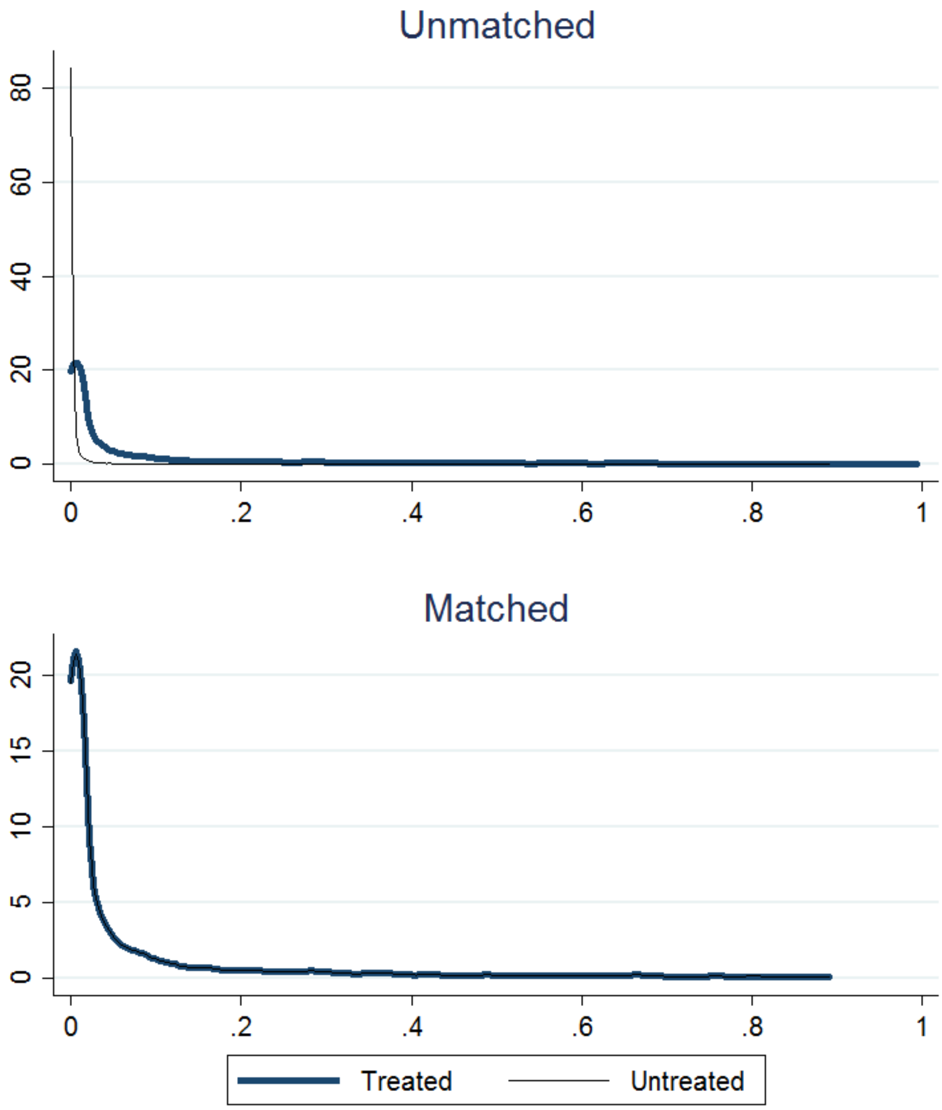
Notes: Estimation based on Gateway to Research (GtR) and the Business Structure Database (BSD) for the period 2004-2016 for UK based private firms using a logit model with one year lagged control variables. Standard errors (s.e.) reported in parentheses. *** p<0.01, ** p<0.05, * p<0.1. Productivity is proxied by turnover per employee.

Table A2: Matching average balancing test for the propensity score.

Variable	Sample	Mean Treated	Mean Control	Bias Std. Bias	Bias Red. Bias	Equality of Means t	Equality of Means p>|t|	Ratio of var. Residuals
log(Employment)	unmatched	3.006	1.132	118.20		220.66	0.000	7.98
	matched	3.352	3.338	0.90	99.3	0.35	0.724	0.99
log(Lab.Productivity)	unmatched	4.361	4.190	14.90		15.63	0.000	1.81
	matched	4.425	4.397	2.40	84.1	1.19	0.235	1.36
log(age)	unmatched	2.400	1.893	57.40		52.49	0.000	1.13
	matched	2.665	2.658	0.80	98.6	0.54	0.587	1.02
Pre-Employment Trend	unmatched	0.076	0.013	27.20		27.55	0.000	2.12
	matched	0.078	0.079	-0.50	98.2	-0.22	0.823	0.81
Pre-Productivity Trend	unmatched	-0.019	-0.021	0.40		0.33	0.743	1.50
	matched	-0.016	-0.026	2.10	473.7	1.12	0.265	1.45
Group	unmatched	0.399	0.088	77.70		97.06	0.000	
	matched	0.453	0.455	-0.70	99.1	-0.28	0.777	
Foreign Owned	unmatched	0.121	0.019	40.70		65.65	0.000	
	matched	0.138	0.129	3.70	91	1.44	0.150	
Science Park Area	unmatched	0.183	0.077	31.90		35.13	0.000	
	matched	0.180	0.192	-3.70	88.5	-1.67	0.096	
Agglomeration Index	unmatched	0.007	0.017	-54.20		-42.58	0.000	0.57
	matched	0.005	0.005	0.40	99.2	0.33	0.738	0.98
Regional R&D Intensity	unmatched	8.916	9.109	-8.90		-7.41	0.000	1.04
	matched	8.869	8.858	0.50	94.5	0.26	0.796	1.01
Competition Index	unmatched	-0.041	0.066	-53.10		-101.84	0.000	7.18
	matched	0.056	0.056	0.30	99.4	0.57	0.569	1.07
Region-Industry Productivity	unmatched	4.744	4.711	6.30		6.22	0.000	1.47
	matched	4.747	4.756	-1.80	71.9	-0.85	0.394	0.97
Region-Industry Employment	unmatched	9.915	11.258	-88.00		-88.68	0.000	1.59
	matched	9.887	9.905	-1.20	98.7	-0.59	0.554	1.11
High-Tech	unmatched	0.054	0.004	30.60		80.76	0.000	
	matched	0.071	0.068	1.80	94.1	0.63	0.528	
Medium-High-Tech	unmatched	0.074	0.003	37.30		114.15	0.000	
	matched	0.094	0.087	3.50	90.5	1.25	0.212	
HKIS	unmatched	0.181	0.175	1.60		1.51	0.131	
	matched	0.188	0.202	-3.60	128.9	-1.85	0.064	
KIS	unmatched	0.474	0.833	-81.40		-91.57	0.000	
	matched	0.509	0.509	0.00	100	0.02	0.985	
Sample Statistics		*R^2*	*$LR\text{-}X^2$*	*$p>X^2$*	*Mean Bias*	*Med. Bias*	*B*	*R*
	unmatched	0.251	20774.9	0	42.9	37.3	165.2	5.04
	matched	0.001	19.61	0.295	1.6	1.2	8.3	1.14

Notes: the second column differentiates between the sample before and after the implementation of the matching technique. Columns 3 and 4 present the mean value of each control variable for firms in the treated and control groups before and after the implementation of the matching technique. In columns 5 and 6 we display the median standard bias across all the covariates included in the logit estimation before and after and the percentage reduction in the bias after the application of the matching procedure. Columns 7 and 8 report the t-tests for the equality of the mean values of firms in the matched sample compared to those in unmatched sample. Column 9 shows the ratio of variance of residuals orthogonal to linear index of the propensity score in treated group over non-treated group. The bottom two rows present a summary of statistics regarding the whole sample: the pseudo R2 from the probit estimation of the treatment on covariates on raw or matched samples and the corresponding X2 statistic and p-value of likelihood-ratio test of joint significance of covariates; the mean and median bias as summary indicators of the distribution of bias across the samples; the Rubin's B shows the absolute standardized difference of means of linear index of propensity score in treated and matched non-treated groups, while the Rubin's R is the ratio of treated to matched non-treated variances of the propensity score index.

Figure A1: Density distribution of propensity score for firms in the treated and control groups before and after the nearest-neighbour matching.



Notes: Estimation of the propensity score based on Gateway to Research (GtR) and the Business Structure Database (BSD) for the period 2004-2016 for UK based private firms using a logit model with one year lagged control variables.

Table A3: Summary statistics of treated firms by category (full sample, manufacturing, services industries, manufacturing high-tech and low-tech knowledge intensive and non-knowledge intensive services industries).

	All Firms	***Manufacturing***	***Services***	***HT***	***LT***	***KIS***	***Non-KIS***
No. Firms	8,943	2,141	6,802	1,169	829	4,309	2,459
Total Value Grants (M £)	9,000	1,170	7,820	968	1,150	7,180	640
Av. No. Projects	2.30	1.20	2.61	1.62	1.23	4.67	1.49
Av. Grant Value (£)	74,223	43,917	82,793	66,199	46,084	150,086	13,722
Av. Grant Intensity	4.04%	1.82%	4.98%	2.33%	1.93%	6.43%	0.92%
Av. No. Partners	23.96	16.25	26.14	22.38	16.76	43.50	8.32
Av. Size	602	391	689	365	405	389	1550
Av. Age	16	21	14	21	21	13	18
Av. Lab. Productivity	4.444	4.827	4.284	4.853	4.805	4.049	4.947

Notes: Statistics based on Gateway to Research (GtR) and the Business Structure Database (BSD) for the period 2004-2016 for UK based private firms before the implementation of the matching algorithm. Total grants value reported in millions of pounds, average grant value in pounds. Grant intensity measured as value of grants received over total turnover. Size measured in number of employees. Productivity is measured as turnover per employee. Manufacturing industry includes all SIC (2003) sectors between 15 and 36, service industry from sector 37 to 95. Following the Eurostat definition, manufacturing high-tech firms have SIC codes (2003) equal to: (24) chemicals and pharmaceuticals; (29) machinery and engines; (30) computers and office machinery; (31) electrical machinery; (32) IT and communication equipment; (33) medical, precision and optical instruments; (34) motor vehicles; (35) transport equipment. Knowledge-intensive services (KIS) include the following sectors: (61) water transports; (62) air transports; (64) post and telecommunications; (65) financial intermediation; (66) insurance; (67) auxiliary activities to financial intermediation; (70) real estate; (71) renting of machinery and equipment; (72) computer related activities; (73) research and development; (74) other business activities; (80) education; (85) health and social work; (92) recreational, cultural and sporting activities.

Table A4: Impact of participation in publicly-funded research projects on UK firms' performance – ATT effects with Kernel matching technique.

Kernel		***All***	
		ST	***MT***
Employment	*ATT*	0.088***	0.221***
	b.s.e.	(0.005)	(0.012)
Turnover	*ATT*	0.048**	0.254***
	b.s.e.	(0.020)	(0.052)
Labour Productivity	*ATT*	0.012	0.037**
	b.s.e.	(0.010)	(0.018)
Untreated		2,968,214	1,352,176
Treated		5,656	3,654

Notes: Estimation based on Gateway to Research (GtR) and the Business Structure Database (BSD) for the period 2004-2016 for UK based private firms. ATT effect estimated using a difference-in-differences technique with propensity score nearest-neighbour matching procedure. Bootstrapped standard errors (b.s.e.) with 500 replications reported in parentheses. *** p<0.01, ** p<0.05, * p<0.1. The number of firms included in the treated and control groups is reported. Labour productivity is measured as the natural logarithm of turnover per employee. Short-term includes years from time t to t+2, medium-term goes from time t+3 to t+5.

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