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Knowledge to money: Assessing the business performance effects of publicly-funded research and innovation grants

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ABSTRACT

UK Research Councils (UKRCs) spend around £3bn pa supporting R&D and innovation. We provide a comprehensive assessment of these grants on the performance of participating UK firms, using data on all projects funded by the UKRCs over the 2004 to 2016 period and applying a difference-in-difference with propensity score matching approach. We exploit the richness of the data available in the Gateway to Research database by investigating the heterogeneous effect of these projects across several novel directions which have not been explored before. We find a positive effect on the employment and turnover growth of participating firms, both in the short and in the long run. Exploring impacts across different types of firms we find stronger performance impacts for firms in R&D intensive industries and for smaller and less productive firms. We also consider how impacts vary depending on the characteristics of the funded research projects in terms of partners characteristics, prior receipt of other research grants and grant value. Finally, we focus on the different sources of grants, analysing in particular the evolution in the funding strategy of Innovate UK. Our results have implications for the extent and targeting of future Research Council funding both in the UK and elsewhere.

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Keywords: Public support; R&D; innovation; Research Council; UK.

JEL Codes: O30, O25, O57

CONTENTS

INTRODUCTION

Through its publicly-funded Research Councils (UKRCs), the UK invests around £3bn pa in supporting R&D and innovation. 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 pa by 2020. To date, assessments of the impact of UKRC grants have been largely partial and 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[1]. However, several previous reviews provide 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 looks 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). Although somewhat mixed, this literature has generally supported the existence of a positive relationship between public R&D support, innovation and firms' growth (Aguiar and Gagnepain, 2017).

In this study we provide the first comprehensive analysis of the effects of UK public support for R&D and innovation on the performance of UK firms. We draw on funding and partnership data from the Gateway to Research (GtR) portal which provides information on funding provided by all of the UK Research Councils over the 2004 to 2016 period as well as the characteristics of the partners involved in each research project. Of particular importance in terms of business engagement with the UKRCs are Innovate UK, which provides grants to firms and other organisations to support innovation, and the Engineering and Physical Science Research Council (EPSRC), which funds university research often in collaboration with industry. We match data from GtR with data on business performance taken from the Business Structure Database, which provides longitudinal data on

[1] For example, Scandura (2016) examines the impact of projects funded by the Engineering and Physical Sciences Research Council, while Frontier Economics (Frontier Economics 2017) focussed primarily on the business impacts of Innovate UK support.

business performance for all UK firms in terms of employment, turnover and productivity growth.

Our study responds to the call by Scandura (2016) for more extensive research on the performance effects of publicly-funded scientific research, and arguments for more extensive access to and use of administrative data for research, by the OECD[2], Card et al. (2011) addressing the National Science Foundation[3], ISTAT[4] and the UK Data Forum[5]. In extending the existing evidence base, we make four main contributions. First, we provide the first comprehensive assessment of the business performance impacts of public science investments in the UK, comparing the heterogeneous effects across sectors, regions, firms' scale and productivity. Secondly, we exploit the richness of the data provided by the GtR portal exploring the different characteristics of the Research Council (RC) funded research projects, particularly in terms of the intensive and extensive margins of the projects in which firms participated and the characteristics of partners. Third, thanks to the longitudinal data on both firm performance and grant receipt, we are able to assess the dynamic relationship between firms' participation to RC-funded projects and firms' growth in the short and medium-term. Finally, we disentangle the effect of participating in research projects funded by different RCs, mainly focusing on the two RCs most directly involved with private firms - EPSRC and Innovate UK. We

2 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

3 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

4 "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.

5 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/.

pay particular attention to the evolution of Innovate UK funding, considering the role the agency assumed after the closure of the English Regional Development Agencies in 2012.

We employ a difference-in-difference propensity score matching technique to analyse the differences in performance between firms who participated in RC-funded projects and a matched comparator group of firms which received no support. Comparing their performance before and after project participation, we are able to estimate the causal effect of publicly-funded research grants on the performance of participating firms. Our assessment takes into account firm heterogeneity in terms of size, past performance and innovative activities, productivity and other factors influencing the self-selection of firms into publicly-funded R&D projects.

Our results show that participating in RC-funded projects had a positive impact on firms' growth. Participating firms grew around 6% faster in the short-term and almost 24% faster in the medium-term compared to non-participating firms. This positive growth effect is particularly strong in manufacturing and in the most R&D intensive regions and industries, helping in particular smaller and less productive firms to scale up quickly. Both single and serial grant holders benefit from publicly-funded R&D projects, mainly when collaborating with domestic and industrially related partners. Larger grants do not seem to increase the economic growth of participating firms, suggesting that smaller grants play a relatively more significant role in fostering firm growth, particularly for small firms. We find evidence of heterogeneous effects across RCs, highlighting the major role played by EPSRC and Innovate UK. Focusing on Innovate UK funded projects, we find a strong positive effect on the growth of supported SMEs particularly after 2012.

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. Section 6 concludes summarising the key results, and presenting some policy implications.

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 by more strategic objectives linked to a desire to build capacity in specific sectors, technologies or localities. In either case 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 and innovation

The key rationale for providing public support for private R&D and innovation is the potential impact on knowledge and value creation. The existing literature has identified four mechanisms which may link public R&D support for firms to increased innovation activity and economic performance.

First, public R&D support will increase liquidity and financial slack in recipient companies which may help to overcome innovation risk and increase the likelihood that a firm will undertake risky projects such as innovations (Zona 2012). Slack resources may also have negative effects, however, as managers are insulated from market realities, encouraging inertia or poor resource allocation towards highly risky projects (Nohria and Gulati 1996). These opposing effects suggest the potential for an inverted U-shape relationship between slack and innovation, where too little slack hinders innovation, while too much may reduce firms' incentives to innovate, with the potential risk of over-subsidising innovation and increasing grant dependency (Kilponen and Santavirta 2007).

Second, through cost-sharing, public support for private R&D and innovation reduces the required investment and de-risks private investment. Profit maximising models of firms' decision to innovate suggest that the go/no-go decision will be linked positively to anticipated post-innovation returns, and negatively related to the perceived risks associated with the project (Calantone et al. 2010; Mechlin and

Berg 1980). The perceived risks associated with a project will itself reflect both the technologies involved, and concerns about the commercial viability of any resulting innovation in terms of expected sales and profitability (Keizer and Halman 2007; Roper, Du, and Love 2008; Cabrales et al. 2008). Technological innovation risks relate to situations where development projects fail to achieve the desired technological or performance outcomes, where innovations prove impossible to deliver in a cost-effective manner (Astebro and Michela 2005), or where there are issues around project duration (Menon, Chowdhury, and Lukas 2002; Von Stamm 2003). Commercial risks associated with innovation may relate to uncertain demand (Astebro and Michela 2005), or issues around rivalry or appropriability (Fosfuri and Giarratana 2009; Leiponen and Byma 2009). The technological and market related elements of innovation risk are interlinked. Radical innovation projects, for example, are more complex in both technological and managerial terms (Keizer and Halman 2007). 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 and innovation 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 or pure knowledge spillovers and economic growth (Beugelsdijck and Cornet 2001).

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

A large body of literature provides empirical evidence on 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 inputs such as R&D investments (see Table A1). Zuniga-Vicente et al. (2014), reviewing more than seventy empirical studies on the relationship between subsidies and R&D investment, conclude that the large majority of studies find a positive effect with 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. Another review by Becker (2015) concludes that the policy additionality effect is particularly strong 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. Becker (2015) also concludes that more recent literature suggests a shift away from earlier findings that public subsidies can crowd out private R&D towards evidence that subsidies typically stimulate private R&D, one reason being the availability of new econometric techniques that control for sample selection bias. In a more recent review of more than fifty micro-level studies published since 2000, Dimos and Pugh (2017), using a meta-regression analysis, also investigate the effectiveness of R&D subsidies on either firms' R&D input or output. Despite the lack of conclusiveness of the evaluation literature, this review rejects any crowding-out effect of private investment by public subsidies, but also finds no evidence of substantial additionality. In addition, the authors also stress the importance of controlling for 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).

In addition, the most recent literature has pointed out how 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 in businesses offsets risk-aversion, and encourages various types of investment in innovation especially through recessionary periods.[6] In terms of analyses of specific R&D programmes, the European Union Framework Programs have attracted much attention, with several studies analysing the impact on innovation inputs (Czarnitzki and Lopes Bento 2013; Czarnitzki and Lopes Bento 2014). Positive additionality is also found in studies analysing public support programmes in Spain, Flanders, France and Korea (Gonzales et al. 2005; Hottenrott and Lopes-Bento 2014; Bedu and Vanderstocken 2015; Cin et al. 2017; respectively). Overall, while conceptual arguments are ambiguous, the balance of empirical evidence therefore suggests a positive link between financial resources and innovation input.

The effect of public R&D and innovation support on innovation outputs has also received considerable attention in the literature, albeit less than that on innovation inputs. Similarly to Zona (2012) for innovation inputs, Marlin and Geiger (2015) for instance in their analysis of US manufacturing firms emphasise how firms can combine bundles of uncommitted resources to improve innovation outcomes. Becker et al. (2016) 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, between public R&D support and innovation outcomes dependent on firms' size and internal capabilities (Lee 2015). Recent studies identifying positive effects on innovation output as measured by companies' patenting activities or applications include Czarnitzki and Lopes-Bento (2014), Doh and Kim (2014), Howell (2017) and Wang et al. (2017). Other studies use R&D employment or R&D jobs as innovation output measures. For instance, Czarnitzki and Lopes-Bento (2013) have reviewed the value-for-money 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

[6] 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 (see below elaboration on collaborative projects).

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.

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 (see Table A2).

The first papers in this field focused mostly on United States innovation and technology programs, providing mixed evidence of impacts on productivity and profitability (Lerner 1999; Wallsten 2000; Feldman and Kelley 2003). Positive performance effects of the European Union Framework Programs have been identified by Bayona-Sáez and García-Marco (2010), for example. Overall, the range of these studies is broad, and the results are again mixed. Some studies find that subsidy recipients achieve higher innovative productivity and are more likely to improve their financial performance (Lerner 1999; Zhao and Ziedonis 2014; Howell 2017). 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), and value added (Duch et al. 2009). However, other studies suggest that public innovation grants do not significantly improve firms' productivity, employment growth or export performance (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, Criscuolo et al. (2016) examining 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 manufacturing jobs. However, this effect seems to exist solely for small firms, which experience a higher probability of entry and larger investment, without any 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 SMEs in South Korea. Controlling for counterfactual outcomes employing a difference-in-difference (DID) methodology, the authors find significant evidence of positive effects of the public R&D subsidy on the productivity of Korean manufacturing SMEs. However, Wang et al. (2017) using administrative data on applications to China's Innofund program, find no evidence that receiving an innovation grant boosts performance in terms of survival or venture funding.

Among the reasons for the heterogeneity of the results of studies analysing the effects of public support on innovation inputs, outputs, and firm performance, perhaps the most important are that the design and implementation of subsidy programs varies markedly across countries, regions, industries, and time periods, and that researchers use different methods and units of analysis in their studies (Klette et al. 2000). Furthermore, differences in the R&D stage at which funding occurs may explain differences in results. For instance, Hottenrott et al. (2017) find that research grants have stronger impacts than development grants, while Clausen (2009) concludes that research subsidies stimulate private R&D, while development subsidies act as a substitute.

Another possible explanation for the lack of consistency in the empirical findings on the additionality of public R&D and innovation support is the limited theory available which predicts the types of effects which should arise from 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 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. Both selection and matching are key methodological issues which have to be considered in order to properly evaluate the effectiveness of public support to private R&D.

There are also a growing number of studies examining the effects of subsidies on high-tech entrepreneurship. Colombo et al. (2012), for instance, find that selective, in contrast with automatic, national support schemes have a significant and large positive effect on the employment growth of young, i.e. up to 5 years old, new technology-based firms (NTBFs) in Italy. The effect on more mature such firms (6-25 years) is negligible, as is the effect of automatic schemes on NTBFs of either age group.[7] The authors point out that automatic support schemes are not offered in all countries, and indeed the majority of research on the effect of subsidies has considered selective schemes, as we do in our analysis below. Using a similar sample, Colombo et al. (2013) find that public subsidies can help small NTBFs to persistently remove the financial constraints that restrict their capital investment activity. Related to NTBFs are young innovative companies, a concept introduced by the European Commission (EC-DG ENTR 2009)[8] in a move to reinforce policies towards potential radical, rather than incremental, innovators in the light of the anticipated positive effects on productivity. Czarnitzki and Delanote (2009) show in a sample of Flemish firms, that young innovative firms grow faster than NTBFs and small young firms, indicating that the R&D requirement matters.

Finally, another strand of the policy evaluation literature considers the differences between public innovation policies aimed at helping individual firms' projects compared to 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, analysis of collaborative R&D projects indicates that alongside the benefits there might also be significant drawbacks associated with research alliances, such as these costs of finding suitable partners, coordinating and managing research networks, possible leakage of innovation and technologies,

7 However the authors emphasize that only 12% of the subsidisation events recorded in the data involved a selective subsidy for a young NTBF.
8 The EC defines these as companies that are less than 6 years old, have fewer than 250 employees, and are highly R&D-intensive, which in turn is defined as R&D spending accounting for more than 15% of a company's total operating expenses. In comparison, NTBFs should only have an R&D intensity larger than zero.

free-riding and opportunistic behaviours (Grimpe and Kaiser 2010; Lokshin et al. 2011; Hottenrott and Lopes-Bento 2016; Bellucci et al. 2016).

In terms of the effects on innovation inputs, Bellucci et al. (2016) focus on the effectiveness of regional R&D policies designed to support firms' individual projects on the one hand, or collaborative R&D ventures between firms and universities on the other hand. Using a difference-in-difference approach the authors show that the supported individual projects are successful in stimulating additional R&D investment. On the contrary, public support to firm-university collaboration seems to have weaker but nonetheless positive effects on the same measure of innovation input. 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 firms' R&D expenditures per employee. She also measures the effects on innovation output, identifying a positive and significant impact on the share of R&D employment two years after the end of projects.

The empirical literature analysing the impact of subsidies for R&D collaboration on firms' economic performance has also resulted in mixed results, although 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. Considering the selection process for the participation of firms into this type of cooperative project, their empirical analysis confirms that subsidised R&D cooperation has a positive impact on the growth of intangible fixed assets, with indirect positive effects on the productivity of participating firms. Aguiar and Gagnepain (2017) have analysed 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 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) find weaker effects on firm performance from support to individual projects or support to collaborative R&D ventures between firms and universities, than on innovation as elaborated earlier. 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 projects (Du et al. 2014).

While the empirical evidence on the business performance effects of public support for R&D and innovation is not entirely consistent it suggests several expectations for our empirical analysis. First, the balance of evidence suggests we might expect to find a positive linkage between UK Research Council funding and subsequent business performance (Hottenrott and Lopes-Bento 2014; Bedu and Vanderstocken 2015; Von Ehrlich and Seidel 2015; Criscuolo et al. 2016; Duch et al. 2009; Doh and Kim 2014; Zuniga-Vicente et al. 2014). Second, we might anticipate stronger additionality for smaller firms where Research Council funding may be more important in releasing financial and other resource constraints (Becker 2015). Third, additionality may also be stronger in more technology intensive sectors where firms have greater internal R&D resources and more capacity for collaborative research or innovation with universities or other partners (Love, Roper, and Bryson 2011; Woerter and Roper 2010; Rantisi 2002; Petruzzelli 2011; Laursen and Salter 2006; Bellucci et al. 2016).

DATA and METHODOLOGY

3.1 UK Research Councils and the Gateway to Research Data

Our analysis covers the years 2006 to 2016, a period during which there were significant changes in the UK innovation and industrial policy landscape (Hildreth and Bailey 2013). In England, Regional Development Agencies (RDAs) with responsibility for promoting economic development were established under the Labour government between 1998 and 2002. The RDAs steadily accumulated responsibilities and, post-2005, had a role in housing, tourism, transport, the provision of business support, attracting inward investment, and providing a range of grants targeted at business improvement, development and innovation in SMEs (Pearce and Ayres 2009). The profile of innovation supports provided by the RDAs varied by region, but typically included Innovation Vouchers, proof-of-concept funding and support for commercialisation through schemes such as Grants for R&D (subsequently renamed 'Smart'). The RDAs were abolished by the Coalition government in 2010-12 and replaced with more localised, business-led, Local Enterprise Partnerships (LEPs) across England (Pike et al. 2018). With the closure of the RDAs, delivery of a range of innovation support schemes for SMEs were transferred to the national Technology Strategy Board (TSB). TSB itself had been established in 2007 to support applied R&D and business innovation by providing grant support to businesses for single company or collaborative R&D projects. After 2010 the number of awards provided by TSB rose rapidly with an increasing focus on smaller firms. In 2014-15, TSB – by then renamed Innovate UK - offered grant funding to 1,401 projects of which around 51 per cent involved university-industry collaboration (Technology Strategy Board 2015)[9]. Innovate UK grant support rates vary depending on the focus of the project and firm size, but can be up to 50 per cent for small firms. In addition to its role in providing grant support for business R&D and innovation, TSB/Innovate UK has also invested significantly since 2010 in the UK's Catapult network, collaborative initiatives to enable firms to access state of the art equipment[10]. One recent study suggests positive survival, turnover and employment benefits from Innovate UK support over the 2008-12 period (Frontier Economics 2017).

While the UK innovation policy landscape changed significantly during our study period there was more stability in the provision of public funding for university R&D and collaborative basic research. The UK's seven Research Councils[11] vary in size, with the most significant in terms of business impact being the Engineering and Physical Sciences Research Council (EPSRC) (Scandura 2016). Originally established in 1994, EPSRC had an annual budget of around £900m towards the end of our study period which is used to fund research (c. £700m) and training and fellowship grants (c. £200m) (Engineering and Physical Sciences Research

9 In 2016, Innovate UK simplified its scheme portfolio focussing the majority of support through a series of sectorally-focussed competitions for grant funding (Innovate UK 2016).
10 See https://catapult.org.uk.
11 That is 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).

Council 2015). Individual EPSRC research projects are university-led, often involving business collaborators and are selected for funding on a competitive basis. EPSRC funding is provided only to university partners, with business partners either making financial or in-kind contributions (e.g. equipment use or staff time) to a project. Evidence of the impact of EPSRC support on participating firms is relatively limited although Scandura (2016) provides evidence of input additionality in terms of both R&D expenditure and employment two years after the end of EPSRC projects.

For our analysis we draw on funding and partnership data from the Gateway to Research (GtR) website[12] developed by the UK Research Councils. GtR provides information on all publicly funded research projects over the 2004 to 2016 period, including data from Innovate UK, the seven Research Councils and the National Centre for the Replacement, Refinement and Reduction of Animals in Research (NC3Rs). GtR also provides information about approximately 34,000 organizations that participated in publicly-funded innovation and R&D projects, including details on the number and value of funded projects, the number and characteristics of partners, the topics and outcomes of the research projects, the value of grants awarded per year, the Research Council providing the funding, and information about each projects' leaders[13]. The GtR data relates solely to the public funding contribution to each project and does not provide any indication of the contribution by firms or other organizations. UK Research Councils provide research funding through a wide range of schemes. The main interventions are grants, university-industry (U-I) collaborations, followed by training grants, fellowships, innovation vouchers and collaborative R&D projects. In most Research Council funded projects, higher education institutions take the role of project coordinators, while collaborators from national and international industry and other organisations participate as non-funded partners. Innovate UK projects aimed at the commercialisation of innovation operate differently, with much of the funding going

[12] 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

[13] The only public funding for R&D and innovation in the UK not included in GtR regards support 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.

to private companies within and outside of the UK. The focus of awards may also be very different across Research Councils, 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.

A breakdown of the total number and value of projects supported by the UK Research Councils over the period 2004-2016 by funding source is provided in Table 1 and Figure 1 (see Table A3 for variable definitions). Over 13 years the UK Research Councils funded more than 70,000 research projects, allocating almost £32 billion. The largest funders were 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.

The distribution of the number and value of projects funded by UK Research Councils varies according to the type of participating organization. As shown in Table 2, we categorized the 34,000 participating organizations in 10 different categories: private firms, universities, public research institutes, private R&D centres, schools, hospitals, government authorities, charities, cultural organizations and others[14]. The largest group of organizations is that of private firms, with more than 14,500 firms participating in funded projects, followed by public research institutes, universities and charities.

3.2 Firm-level data

In order to evaluate the "*money to knowledge-knowledge to money*" effect of R&D grants awarded by the UKRCs, we matched the GtR data with firm-level data from

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

the ONS Business Structure Database (BSD). This was accessed through the UK Data Service and covers the whole population of businesses in the UK between 1997 and 2016 (ONS 2017).[15] The BSD provides information on firms' age, ownership, turnover, employment, industrial classification at the SIC 4-digit level and postcode. We 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 and turnover growth. Using the Company Reference Numbers (CRNs) provided in the GtR data, we have matched almost 10,000 UK firms who have participated in publicly-funded research projects with the BSD dataset, combining in this way information on project participation and firm-level characteristics.[16]

3.3 Methodology

As our earlier review of literature suggests a significant hurdle in the identification of the causal relationship between R&D grants and the performance of participating firms is the possibility of endogeneity bias. Specifically, participation in research projects is not an exogenous and randomised treatment but is very likely to be affected by endogenous factors influencing allocation decisions and the self-selection of firms into this kind of program.

To overcome this issue we apply a difference-in-difference (DID) propensity score matching (PSM) technique at the firm-level (Lechner 2002; Leuven and Sianesi 2017). Combining PSM with DID, we aim to reduce the selection bias accommodating covariates into a DID framework (Heckman et al. 1997). The matching estimator controls for the selection bias based on observable covariates by comparing treated with comparable untreated firms, while the DID approach controls for the bias associated with unobserved heterogeneity (Imbens 2004).

15 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.
16 For the vast majority of UK firms (more than 80%) the GtR data provided already the CRN number. For the remaining firms we have assigned manually a CRN matching information from Bureau Van Dijk FAME database and the Company House data based on names and full postcodes to distinguish between multiple firms with the same name.

Our identification strategy relies first on comparing the performance of participating firms before and after their participation in the publicly-funded projects, and then on comparing any performance differences to those of a control group of similar but non-participating firms. Through the construction of a valid control group based on the observable differences between participants and non-participants, our matching approach should control for endogeneity bias. The final step is to assess the average treatment effect on the participating firms, the ATT effect, to estimate the difference in the outcome variables between firms which participated in UKRCs projects and firms which did not.

First, we consider time *t=0* as the year in which firms participate in their first publicly funded research project.[17] We then measure the average growth rate of the outcome variables y^1_{t+n}, employment and turnover[18], as the difference between the pre-treatment level at time *t-1* and the short (2 years after treatment) and medium term (5 years after) levels.[19] Since we are interested in identifying the differences in firms' performance after the participation in a research project, we can express the average treatment effect (τ_{ATT}) on performance in terms of performance growth after the start of the project *t+n* as $E(y^1_{t+n}|\, S_t = 1)$, and the counterfactual performance growth for the same group of firms had they not participated as $E(y^0_{t+n}|\, S_t = 1)$:

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

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, i.e. whether the firm has participated in publicly funded research projects $E(y^1_{t+n}|\, S_t = 1)$ or not $E(y^0_{t+n}|\, S_t = 0)$. Hence, we need to build a suitable control group by considering

17 For untreated firms included in the control group t=0 represents their median year in the sample.
18 Due to the limited number of variables included in the BSD database, it is not possible to estimate the impact of UKRC funded research projects on advanced measures of firms' productivity, such as total factor productivity or gross value added. Results considering the impact on labour productivity, measured as turnover per employee, are available from the authors upon request.
19 Superscript 1 in y^1_{t+n} indicates the participation to the project; n denotes the number of years after the start of the project.

instead the effect of no treatment on the performance growth of similar firms which did not participate in funded research projects.

To build the control group we use a propensity score matching technique in order to select suitable controls from the very large group of untreated firms, matching observed characteristics as closely as possible to those of treated firms before the start of the research project (Rosenbaum and Rubin 1983; Heckman et al. 1997; Becker and Ichino 2002). We estimate the probability that any firm participates in a publicly-funded research project, the so-called propensity score, based on a set of relevant observable characteristics which have been found to influence the likelihood of participation in the previous literature. We use a logit model with firm and year fixed-effects to estimate the propensity score for all observations, using several covariates which may explain the probability of participation. We include a set of firm-level variables such as employment, employment squared, turnover, firm age, employment and productivity growth in the 2-years period before the projects have been awarded, firms market share, group membership, foreign ownership and single-plant firm dummies to control for firms' characteristics, and the total number of patents to control for firms' previous innovative activities. In addition, we take into account whether firms are located in the same postcode district as a science park, to control for the potential effect of university spillovers, and the number of other R&D projects publicly-funded by UK Research Councils within the same region and industry to control for potential peer-effects (Lofsten and Lindelof 2002; Siegel et al. 2003; Yang et al. 2009; Vasquez-Urriago et al. 2016).[20] Secondly, 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,[21] the region-industry competition level measured with the net entry-exit rate, region-

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20 Data about the location of science parks in the UK has been drawn from the UK Science Park Association (UKSPA) website.

21 We have measured region and region-industry R&D intensity using data from the UK CIS dataset (BIS-ONS, 2018) as the average ration between R&D expenditure and turnover at the regional NUTS 2-digit level or at the regional NUTS 2-digit and industry SIC 2-digit level.

industry employment and turnover per employee levels and finally year, region (LEP or NUTS 2-digit level) and industry (SIC 4-digit) dummies.[22]

The propensity score estimation results in Table 4 prove consistent with previous studies. In particular, large and younger firms seem to be more likely to participate in research projects funded by the RCs, especially if they are part of a business group and are domestically-owned. In addition, firms' market share and previous patenting activity increase the likelihood of participation. Firms located close to a science park, in more R&D intensive regions and surrounded by other participants to RC projects have also a higher probability of participating in RC-funded projects.

After estimating the probability of participating in a publicly-funded research project, we proceed by matching the untreated and treated observations according to their estimated propensity score. First, we impose a common support condition, dropping the treated and untreated observations whose propensity scores are larger or smaller than the maximum or minimum of the other category. Secondly, we apply a Nearest-Neighbour matching technique with a strict Caliper bandwidth, matching each treated observation only with the closest untreated observation within a 0.05 range in the propensity score. In addition, we restrict 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. To test the sensitivity of the matching method, as a robustness check we apply 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 firms which are further from the propensity score of treated observations within a certain range. Finally, we have clustered the standard errors following the Abadie and Imbens (2011) methodology for the Nearest-Neighbour matching procedure to take into

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22 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.

account the additional source of variability introduced by the estimation of the propensity score (Heckman et al. 1997).[23]

After estimating the propensity score, dropping outliers and keeping only firms which satisfy the common support condition, our final sample contains almost 6,000 UK firms participating in their first R&D project funded by UKRCs and an equal number of similar untreated firms included in the control group. Table 3 presents summary statistics about the average grants value, projects characteristics, size and productivity of firms in our sample by industrial classification. In addition, Figures 2 and 3 report the distribution of the number of treated firms and their average grant intensity across industries (SIC 2-digit) and regions (NUTS 2-digit). The distribution of participating firms and their grant intensity, measured as grant value divided by turnover, is different across industries and regions. For instance, manufacturing industries record the largest share of 'treated' firms, although in terms of grant intensity the main sectors are the machinery, business-to-business and public service provision. Geographically, the distribution in Figure 3 is more even across regions, with higher shares of treated firms and grants intensity in Oxfordshire, Cambridgeshire, the Bristol area, the Midlands and around Edinburgh.

Table 4 reports the results of tests verifying 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 mean differences across the treated and control group for the set of variables used to estimate the propensity score after matching. 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 mostly insignificant, suggesting a consistent and balanced matching, and that there are no systematic differences in the observable characteristics of treated and untreated firms before the participation in publicly-funded research projects. This is confirmed also in Figure 4 showing the presence of similar trends for the two main outcome variables,

23 Standard errors are instead bootstrapped with 500 repetitions for heteroscedasticity consistency when using the kernel matching algorithm.

employment and turnover, between treated and untreated firms before the beginning of the UKRC funded projects at time *t=0*. The matching procedure satisfies the balancing property, suggesting that the conditional independence assumption is not violated, since y^1_{t+n} and y^0_{t+n}, respectively are statistically independent for firms with the same set of exogenous characteristics (Rubin 1977; Rosenbaum and Rubin 1985; Caliendo and Kopeinig 2008). This is confirmed graphically in Figure 5 which shows that the actual and estimated probabilities of participating in UKRC-funded research projects are very similar for both the treated and control groups after the matching.

RESULTS and DISCUSSION

We exploit the richness of our dataset by investigating the heterogeneous impact of RC-funded research projects on the performance of different groups of participating firms. First, we estimate the general effect for the total sample of firms, providing several tests to corroborate the robustness of the results. Secondly, we explore the heterogeneous impact across different participating firms' characteristics, based on firms' size and productivity, regional and industrial distribution. Third, we consider the effect of different RC-funded projects characteristics on the performance of participating firms, specifically considering the number and value of projects participated, and the number and characteristics of participants. Finally, we disentangle the effect of participating in projects funded by different RCs, analysing in particular the evolution in the funding strategy of EPSRC and Innovate UK and their implications for the performance of participating firms.

4.1. General effect and firm heterogeneity

Columns 1 and 2 in Table 5 show that participating in projects funded by RCs has a positive impact on employment and turnover growth of all firms in our sample, both in the short and medium-term. Employment grows on average 6.2% faster in treated firms in the 3 years following the award, and almost 24% in the medium-term. Turnover growth is also positively affected by participation, increasing in the short-run by almost 6% and 23% in the medium-term. These findings are in line with the previous literature, explaining the larger effect in the medium-term due to the time needed to develop new R&D activities after the start of a research project and to commercially exploit the results of new innovations (Barajas et al. 2012; NESTA 2012; Dimos and Pugh 2016). The results for our entire sample period are consistent with additional tests where we focus our analysis only on the post-2008 period (columns 3 and 4),[24] and are robust to using a kernel matching technique instead of the Nearest-Neighbour method (columns 5 and 6) with very similar marginal effects.

Secondly, we analyse potential sector-specific patterns, following the predictions of the conceptual framework, differentiating between manufacturing and services firms[25], high-tech versus low-tech manufacturing firms, and between knowledge intensive services (KIS) and non-KIS companies (Table 6). Overall, participation in RC-funded projects has a similar effect on the employment growth of firms in both manufacturing and services industries, increasing it by around 24% after 6 years, however turnover growth is faster for manufacturing companies increasing by almost 30% in the medium-term, compared to only 17% in service firms. The differences in the magnitude of the ATT effect are even more striking when differentiating between high-tech/low-tech manufacturing firms and between KIS and non-KIS companies. In fact, as anticipated by previous literature, the effect is much larger for high-tech manufacturing sectors than KIS industries, both in terms of employment and turnover growth (Love et al. 2011; Bellucci et al. 2016). In addition, RC-funded projects have a positive impact also for firms in low-tech manufacturing industries, although smaller in magnitude in respect to high-tech firms, while the effect for non-KIS firms' employment and turnover growth seems to be smaller and significant only in the long-run. Thus, our results suggest that participation in publicly-funded research projects has a positive effect even on the performance of firms in sectors with low average R&D intensity

This evidence is confirmed by the results in Table 7 where we analyse the impact of participating in RC-funded projects for firms across the distribution of industry and region-industry R&D intensity. Note that the positive effect on the employment

24 As a robustness check in columns 3 and 4 we 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.
25 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.

growth of participating firms is much stronger than untreated firms regardless of the industry and region R&D intensity, with similar magnitudes across the four quartiles of the distribution. However, we find evidence that the positive effect on turnover growth is much larger for firms operating in more R&D intensive regions and industries, increasing their total revenue due to RC support in the short-run by almost 13% and in the medium-term up to 48%. These results suggest that RC-funded projects allow firms to expand their operations and to hire new employees regardless of their R&D intensity. However, probably firms in R&D intensive sectors are able to capitalize the results of the publicly-funded research in terms of total sales in the long-run, highlighting the role of internal absorptive capacity in order to convert public money to knowledge and then into new sales and profits (Woerter and Roper 2010; Petruzzelli 2011).

Finally, as suggested by previous studies, the impact of public-funded R&D projects on firms' performance may also vary depending on other firms characteristics (Czarnitzki and Lopes-Bento 2013; Dimos and Pugh 2016; Bellucci et al. 2016; Cin et al. 2017). We therefore evaluate the impact of participation on the performance of firms across the size and productivity distribution of treated and untreated firms (Table 8).[26] It is evident that, as suggested by Becker (2015), smaller and less productive participants experience the largest performance benefits in relation to their untreated counterparts. The impact seems to be particularly large for the least productive companies in our sample which, 6 years after the award, register an employment growth 28% faster than untreated firms and an increase in turnover by more than 45%. More generally, we find decreasing ATT as firm size and productivity increase, and almost no statistical difference in employment and turnover growth between treated and untreated large firms with more than 250 employees.

26 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.

4.2. UKRC Projects Heterogeneity

We now investigate the effect of different projects characteristics on the performance of participating firms. In particular, we consider the number of projects in which firms participated, the number and characteristics of participants, and the value of project grants.

First, in Table 9 we look at the number of RC-funded projects in which firms participated after their first research grant, differentiating between single grant holders, the majority of firms in our sample, and serial-grant participants. As expected, we find a much stronger positive impact for serial-grant participants, increasing their size by more than 30% and their turnover by 38% 6 years after the beginning of their first RC-funded project. However, note from the first two columns in Table 9 that the positive effect of publicly-funded research is significant for firms participating only to one research project. This highlights the benefits of publicly-funded R&D also for firms not usually involved in these projects. By increasing the funding available and the scope of these projects to include new entrants it would be possible to foster the growth of a larger number of firms including those not traditionally participating in publicly-supported projects. In addition, in the last two columns of Table 9, we test the robustness of our results by testing their sensitivity to outliers and removing from our sample firms in the top percentile of the number of projects distribution.[27] After removing these outliers, the results are in line with the estimations for the general sample presented in Table 5, with very similar magnitudes for the ATT effects on employment and turnover growth.

Secondly, in Table 10, we consider the impact that the number of partners in each RC-funded project might have on the performance of participating firms. According to the previous contributions, larger R&D projects could have a more positive impact on the performance of participating firms, mainly by increasing the learning opportunities from a number of different partners, improving the R&D project output and then firms' growth (Belderbos et al. 2004; Okamuro 2007). However, a large number of partners could also reduce the outcome of the R&D collaboration,

[27] Firms in the top percentile of the number of projects distribution have participated during our sample period to more than 7 and up to 85 projects.

increasing uncertainty and the cost of coordination, monitoring and control practices (Morandi 2013). Results in Table 10 suggest that the number of partners in RC-funded projects does not affect the performance of participating firms, since the effect on firm employment and turnover growth is always positive across the distribution of the number of partners, and it is not statistically different across the four different quartiles.

Nevertheless, it can be argued that not the number of partners per se, but their characteristics which might influence the performance of firms participating to RC-funded projects (Du et al. 2014; Hewitt-Dundas et al. 2017). Therefore, in Tables 11 and 12 we investigate the heterogeneous impact of different partners' characteristics on the performance of participating firms. Table 11 differentiates between firms participating in RC-funded projects together with other foreign partners or led by foreign leaders. The performance effect proves weaker than for firms only collaborating with domestic partners, both in term of employment and turnover growth. This difference is more striking when comparing foreign-led versus domestic-led projects, finding almost no statistically significant effect for the performance growth of firms participating in RC projects led by foreign organizations. Thus, external knowledge introduced by foreign partners and leaders does not seem to be conductive to better performance for domestic firms participating in RC-funded projects. This effect could be explained by the complexity of the interaction with foreign partners and by the increasing cost of coordination, especially when the leader of the project is geographically and organizationally distant from domestic participants and from the providers of the R&D support (Miotti and Sachwald 2003; Lhuillery and Pfister 2009; D'Este et al. 2013).

We further test this point by analysing in Table 12 the heterogeneous impact of RCs' support on the performance of firms across the distribution of industry relatedness between project partners. We measure relatedness to the rest of the project partners following the methodology proposed by Neffke et al. (2011), using spatial co-occurrence between sectors at the SIC 5-digit level as a measure of industrial relatedness (Jaffe, 1989).[28] Table 12 shows that the positive impact of participation in RC-funded projects on employment, and particularly on turnover, growth is larger as firms' relatedness with the other project partners increases. For instance, the employment growth after 6 years from the beginning of the research project increases from 23% to 28% moving from the bottom to the top quartile of the industrial relatedness distribution, while from 16% to 27% in terms of turnover growth. Therefore, relatedness between projects' partners improves the final outcome of research projects, especially in terms of firm growth. Coherence, rather than diversity, seems to magnify the positive effects of RC support (Sakakibara 2003; Von Raesfeld et al. 2012; D'Este et al. 2013; Van Beers and Zand 2013).

Finally, we contribute to the existing literature by considering the continuous treatment effect of RC grant value on firms' growth. This information is usually not available in most of the previous studies on this topic, and its analysis could shed light on the heterogeneous relationship between publicly-funded R&D projects and participants' performance. Figure 6 reports the continuous treatment effect of RCs' grant value on the short and long-run employment and turnover growth of participating firms across five different quantiles of the grants value distribution. Allowing for the difference between treated and untreated firms, a positive and significant effect on employment and turnover growth is evident across the different quantile of the grants value distribution, with an overall magnitude in line with the results estimated in our general sample. The effect of smaller grants is marginally greater although not statistically different from the other quantiles.

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[28] We first estimate industrial relatedness between each pair of sectors *s* and *j* using BSD data on the population of UK firms (ONS, 2017) and co-occurrence analysis started by Jaffe (1989) and broadly developed since (Teece et al. 1994; Hidalgo et al. 2007; Bryce and Winter, 2009). Specifically, we investigating the frequency with which firms in industries s and j co-locate in the same regions, relative to all other industries, using a cosine index. Co-occurrence analysis measures the relatedness between two industries by assessing whether two industries are often found together in the same economic entity. The assumption made is that the frequency by which two industries are jointly located in the same regions can be interpreted as a sign of the strength of their relationship, in terms of production processes and technologies adopted, input-output linkages and skills required. After calculating the relatedness between each pair of industries, we estimate a measure of industrial closeness of a firm to the rest of the project's partners creating an indicator function that takes the value 1 if the relatedness between the firm and each other partner in the project is above the mean or not. We then calculate the ratio of close relations over the total number of possible relations in the project.

4.3. UK Research Councils Heterogeneity

Another feature of our data is that we are able to analyse the efficiency of research projects funded by different UK Research Councils, comparing their heterogeneous effect on the performance of participating firms. We focus our attention mainly on the grants awarded by the two main bodies responsible for the largest part of grants involving private firms as shown in Figure 1: Innovate UK and the Engineering and Physical Science Research Council (EPSRC). The performance impact on firms participating in R&D projects supported by these two bodies could differ systematically given the different focus and target of their policy intervention. Innovate UK provides support to private firms with a focus on reducing R&D risks, enabling and supporting business innovation and the commercialization of R&D outputs. By contrast, the EPSRC focuses mainly on the support of universities' basic and applied research, i.e. well before the commercialization phase of innovation, and extends only to private firms which collaborate with funded universities in U-I partnerships.

Table 13 distinguishes the evaluation analysis between firms involved in university-industry collaborations funded by the EPSRC, by the Medical Research Council (MCR), firms' research projects funded by Innovate UK and the remaining R&D projects funded by other RCs. Most of the treated companies received support from Innovate UK, more than 4,000, while EPSRC-supported U-I collaborations involving about 900 of the firms in our sample. Firms involved in projects funded by EPSRC seem to benefit mainly in terms of employment growth, increasing their scale by 24.3% in respect to comparable non-treated firms six years after the start of the project, while experiencing no turnover growth in the short run and a 26% increase after 6 years. On the contrary, firms supported by Innovate UK experience performance growth compared with their untreated counterparts in terms of employment (+6%/+23%) and turnover growth (+6%/+21%) both in the short and in the medium term. Employment and turnover growth are limited to the long-run also in the case of research projects supported by the MRC, while there is almost no significant effect for the performance of firms supported by other RCs.

These heterogeneous effects across UKRCs could be driven by the different categories of firms supported by different RCs and by their funding strategies and focuses. To disentangle this, in Table 14 we estimate the treatment effect across different Research Councils and participating firms' size, focusing on the two main RCs supporting private firms, EPSRC and Innovate UK. In both cases, the effect is much larger for micro and small firms, finding particularly strong impacts on the employment and turnover growth of micro and small firms supported by EPSRC 6 years after the beginning of the research project. In addition, in Table 15 we try to disentangle the effect of collaborating in a RC-funded project together with a university by looking only at Innovate UK projects in which university-industry collaborations are not involved. Again, we do not identify any major difference in the performance of Innovate UK supported firms collaborating or not with universities, suggesting that university-industry collaboration is not the driver of this heterogeneous effect.

Finally, we focus our attention on projects supported by Innovate UK in order to analyse the dynamic evolution of its funding strategy especially after 2012. In fact, as previously discussed in section 3 and as documented in Figure 7, after the abolition of the Regional Development Agencies (RDAs) in 2012, a range of innovation support schemes were transferred to Innovate UK, shifting its focus towards the support of SMEs. These became almost 90% of the total number of firms supported between 2013 and 2015. Therefore, in Table 16 we test whether the shift in the funding strategy of Innovate UK in 2012 has had any effect on the performance of supported SMEs. First, we compare the impact on the performance of SMEs supported by Innovate UK before and after 2012 in the first 4 columns of Table 16. Both before and after 2012, SMEs supported by Innovate UK research projects experienced faster employment and turnover growth than comparable unaffected SMEs, but there is no statistically significant difference in the performance effect between the two periods as documented by the insignificant results in Table 16, columns 5 and 6. However, in the last four columns in Table 16 we see a significant difference in the economic performance of SME and non-SME firms supported by Innovate UK after the shift in policy in 2012. In fact, while there is no statistically significant difference in the economic growth of SMEs and large firms supported by Innovate UK before 2012, in the last two columns we find evidence of a much stronger and statistically significant positive impact of Innovate UK support for the employment and turnover growth of SMEs rather than large firms after 2012. This evidence clearly indicates that the shift in Innovate UK focus after 2012 had a significant impact on the performance of supported SMEs and large firms, increasingly targeting a larger number of SMEs with relatively smaller grants, and fostering the innovativeness and economic growth for a broader sample of SMEs.

CONCLUSIONS

Over the last decade UK Research Councils have invested more than £3bn pa in supporting R&D and innovation projects. To date, assessments of the impact of this public investment have been partial, often relying on limited information in innovation surveys or focused on specific Research Councils (Scandura 2016; Frontier Economics 2017). In this study for the first time we provide a comprehensive assessment of UK public support for R&D and innovation, assessing the impact of participation in publicly-funded research grants on the performance of UK firms.

Our analysis is based on data on all R&D and innovation projects funded by UK Research Councils over the 2004 to 2016 period taken from the Gateway to Research database and firm-level data from the Business Structure Database. We apply a difference-in-difference, propensity score matching technique to evaluate the performance of UK firms who participated in publicly-funded R&D and innovation grants compared to a matched comparator group which received no support.

Our analysis suggests four main conclusions. First, firms involved in projects grew 6% faster in the short-term and 24% in the medium-term, than similar firms which did not participate to UKRC projects. Second, this effect is stronger in manufacturing industries and in the most R&D intense regions and industries, in particular for smaller and less productive firms. Third, benefits from publicly-funded R&D projects are significant in particular when collaborating with domestic and industrially related partners, regardless of the number or size of projects. Fourth, business growth is mainly driven by EPSRC and Innovate UK support, with a particularly relevant role played by Innovate UK in fostering SMEs growth after the closure of the Regional Development Agencies in 2012.

Overall, our analysis shows that public support by RCs has a strong positive impact on participating firms' growth in the short and medium term. Our results echo those of other studies which have suggested – albeit on the basis of a more partial assessment – the benefits of public support for private R&D and innovation. For the UK, where recent policy announcements point to significant increases in public support for private R&D and innovation, our results are reassuring.

Our results also suggest some guidelines for maximising the additionality of public support for R&D and innovation. First, our results suggest – perhaps unsurprisingly - that impacts are largest in R&D intensive sectors. Second, our analysis suggests that growth impacts are greatest in smaller firms and in those with lower productivity, and that growth effects in high productivity firms are small. This result suggests some trade-offs. Maximizing additionality and growth impacts would suggest targeting support on smaller, less productive firms while maximizing the impact on knowledge creation and new-to-market innovation would suggest targeting leading-edge, higher productivity businesses: here, however, additionality may be more limited. Policy in the UK currently focusses on supporting excellence in R&D and innovation, with resources allocated primarily through thematic competitions for funding. This results in a concentration of support in higher productivity businesses. Indeed, during our study period, our analysis of the Gateway to Research database suggests that 65% of public support for business R&D and innovation was allocated to firms in the top quartile of the productivity distribution, where our results suggest that both additionality and growth effects were limited.

Our study is subject to a number of limitations. 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 of public support for R&D and innovation on firms. Spillovers or multiplier effects may significantly enlarge these effects, while displacement or competition effects may reduce them (Roper, Love, and Bonner 2017). 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. Fourth, despite all the robustness tests provided to assess the overall quality of our methodological approach, our identification strategy could still be affected by unobservables endogeneity bias. Further research is needed to investigate new approaches to improve the identification strategy. Finally, our study focusses only on UK public support for R&D and innovation. International evidence from similar on-going studies may provide alternative perspectives reflecting different grant allocation mechanisms and selection priorities.

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: Number and average value of projects funded by UK Research Councils by participants organization type

	Firms	*Government*	*Universities*	*Public R&D Inst.*	*Private R&D Inst.*
No. Organizations	14,854	747	543	847	68
Av. No. Partners	10.79	18.38	13.33	18.26	21.29
Av. Grant Value (£)	98,104	77,205	97,446	179,220	97,632
Av. No. Projects	2.40	6.14	109.77	9.00	18.40
	Hospitals	***Schools***	***Charities***	***Cultural Org.***	***Others***
No. Organizations	423	256	1,680	490	785
Av. No. Partners	133.43	15.22	23.75	15.34	20.12
Av. Grant Value (£)	93,292	123,422	114,484	32,315	165,318
Av. No. Projects	4.14	40.09	2.84	2.64	2.56

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

Table 3: Summary statistics of treated firms by category

	All Firms	***Manufacture***	***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 4: Propensity Score estimation and matching average balancing test.

	Propensity Score		*Mean*		*Bias*	*t-test*		*Var.*
	Coeff.	*s.e.*	*Treated*	*Control*	*Perc.*	*t-value*	*p-value*	*Ratio*
Employment	0.332***	(0.005)	3.3396	3.334	0.4	0.14	0.886	0.99
Empl. Sq.	0.00008*	(0.00001)	1.8e+7	1.6e+7	1.2	1.21	0.225	1.67
Lab.Prod.	-0.00502	(0.0057)	4.4179	4.4145	0.3	0.15	0.883	1.27
Age	-0.126***	(0.0101)	2.6629	2.6569	0.7	0.44	0.656	1
Empl. Growth	0.0227	(0.0232)	0.07855	0.07357	2.2	1.01	0.313	0.92
Lab.Prod. Growth	0.0250*	(0.0137)	-0.01608	-0.01242	0.8	0.41	0.679	1.38
Group	0.165***	(0.0151)	0.45046	0.45259	0.5	0.23	0.82	.
Foreign Owned	-0.159***	(0.0227)	0.13601	0.13246	1.4	0.55	0.58	.
Market Share	0.733***	(0.1280)	0.03197	0.03028	2.2	0.83	0.408	1.07
Single Plant	0.0203	(0.0149)	0.35671	0.35423	0.6	0.28	0.783	.
Tot. Patents	0.278***	(0.0160)	0.14018	0.18777	10.8	3.35	0.001	0.63
Science Park	0.221***	(0.0149)	0.18093	0.20614	7.6	3.39	0.001	.
Peer Effect	0.0008***	(0.0001	50.451	53.05	2.6	2.36	0.018	0.85
Aggl. Index	1.861***	(0.7160)	0.00528	0.00539	0.6	0.44	0.658	1.01
Reg. R&D Int.	0.00502	(0.0033)	8.873	8.9118	1.8	0.93	0.353	0.95
Competition Index	0.248	(0.1510)	0.05643	0.05812	0.8	1.52	0.128	0.99
Reg-Ind. Lab.Prod.	-0.0475**	(0.0234)	4.7451	4.7278	3.3	1.61	0.107	1.03
Reg-Ind. Empl.	-0.0946***	(0.0116)	9.8908	9.9127	1.4	0.72	0.474	1.05
Sample Statistics	*R^2*	*LR-Chi^2*	*p.chi^2*	*Mean Bias*	*Med. Bias*	*B*	*R*	*No. Obs.*
	0.002	35.64	0.005	2.2	1.3	11.2	0.78	11,264

Notes: The second and third columns report the results of the propensity score estimation using a logit model. Robust standard errors (s.e.) reported in parentheses. *** p<0.001, ** p<0.01, * p<0.05. Columns 4 and 5 present the mean value of each control variable for firms in the treated and control groups after the implementation of the matching technique. In column 6 we display the median standard bias across all the covariates included in the logit estimation after the matching procedure. Columns 7 and 8 report the t-tests for the equality of the mean values between treated and untreated firms in the matched sample. Column 9 shows the ratio of variance of residuals orthogonal to linear index of the propensity score in treated group. The bottom row presents a summary of statistics regarding the whole sample: the pseudo R2 from the logit estimation and the corresponding X^2 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. Finally the total number of treated and control observations in the support sample.

Table 5: Impact of participation in publicly-funded research on UK firms' performance – General sample and robustness

	General - NN		After 2008		General - Kernel	
	ST	MT	ST	MT	ST	MT
Employment	0.0620***	0.242***	0.0572***	0.202***	0.0968***	0.198***
	(0.00871)	(0.0189)	(0.00913)	(0.0209)	(0.00578)	(0.0125)
Turnover	0.0590**	0.233***	0.0597***	0.156***	0.127***	0.270***
	(0.0187)	(0.0370)	(0.0181)	(0.0385)	(0.0129)	(0.0252)
No. Treated	5632	3642	4380	2416	5632	3642

Notes: Estimation based on Gateway to Research (GtR) and the Business Structure Database (BSD) for the period 2004-2016. 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 for the Nearest-Neighbour matching, while bootstrapped standard errors for the Kernel matching. *** p<0.001, ** p<0.01, * p<0.05. The number of firms included in the treated group is reported. Short-term refers to growth between t-1 and t+2, medium-term between t-1 and t+5.

Table 6: Impact of participation in publicly-funded research on UK firms' performance – Manufacturing and services industries

	Manufacturing		**Manuf. - HT**		**Manuf. - LT**	
	ST	MT	ST	MT	ST	MT
Employment	0.0653***	0.243***	0.102***	0.306***	0.0653***	0.243***
	(0.0146)	(0.0464)	(0.0184)	(0.0500)	(0.0146)	(0.0464)
Turnover	0.0757	0.293***	0.148**	0.379***	0.0757	0.293***
	(0.0435)	(0.0768)	(0.0491)	(0.0818)	(0.0435)	(0.0768)
No. Treated	1,548	1,088	630	416	918	672
	Services		**KIS**		**Non-KIS**	
	ST	MT	ST	MT	ST	MT
Employment	0.0591***	0.237***	0.0672***	0.249***	0.0323	0.175***
	(0.0102)	(0.0207)	(0.0117)	(0.0244)	(0.0202)	(0.0426)
Turnover	0.0268	0.172***	0.0644*	0.172**	0.0398	0.153**
	(0.0231)	(0.0473)	(0.0327)	(0.0644)	(0.0282)	(0.0536)
No. Treated	3,978	2,488	2,883	1,815	1,082	662

Notes: Estimation based on Gateway to Research (GtR) and the Business Structure Database (BSD) for the period 2004-2016. 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<0.001, ** p<0.01, * p<0.05. The number of firms included in the treated group is reported. 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 refers to growth between t-1 and t+2, medium-term between t-1 and t+5.

Table 7: Impact of participation in publicly-funded research on UK firms' performance across region-industry R&D intensity

	Industry R&D Intensity							
	1st		2nd		3rd		4th	
	ST	MT	ST	MT	ST	MT	ST	MT
Employment	0.0262	0.185***	0.0615**	0.203***	0.0718***	0.294***	0.0780***	0.258***
	(0.0146)	(0.0332)	(0.0212)	(0.0548)	(0.0192)	(0.0451)	(0.0172)	(0.0359)
Turnover	0.0122	0.163	0.113*	0.216*	0.0455	0.207*	0.0988**	0.319***
	(0.0435)	(0.102)	(0.0466)	(0.0930)	(0.0467)	(0.0851)	(0.0383)	(0.0708)
No. Treated	1,960	1,160	848	547	1,013	658	1,348	930
	Region-Industry Peer Effect							
	1st		2nd		3rd		4th	
	ST	MT	ST	MT	ST	MT	ST	MT
Employment	0.0588***	0.225***	0.0575**	0.249***	0.0907***	0.263***	0.0957***	0.244***
	(0.0109)	(0.0265)	(0.0200)	(0.0475)	(0.0219)	(0.0516)	(0.0280)	(0.0585)
Turnover	0.0506	0.169**	0.0177	0.295***	0.0591	0.205*	0.130*	0.486***
	(0.0271)	(0.0583)	(0.0396)	(0.0719)	(0.0503)	(0.0947)	(0.0637)	(0.132)
No. Treated	1,447	1,105	1,461	903	1,457	923	1,248	694

Notes: Estimation based on Gateway to Research (GtR) and the Business Structure Database (BSD) for the period 2004-2016. R&D intensity calculated at the industry (SIC 2) and region-industry (NUTS2-SIC2) level using UK CIS data as average ratio between R&D expenditure and total turnover. 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<0.001, ** p<0.01, * p<0.05. The number of firms included in the treated group is reported. Short-term refers to growth between t-1 and t+2, medium-term between t-1 and t+5.

Table 8: Impact of participation in innovation grants on performance across the size and productivity (turnover per employee) distribution of treated and untreated firms

	Scale Distribution							
	Micro		Small		Medium		Large	
	ST	MT	ST	MT	ST	MT	ST	MT
Employment	0.0965***	0.281***	0.0640***	0.242***	0.0169	0.239***	0.0186	0.160**
	(0.0115)	(0.0253)	(0.0151)	(0.0333)	(0.0234)	(0.0492)	(0.0252)	(0.0567)
Turnover	0.0687*	0.230***	0.0785*	0.235***	0.0789	0.266**	0.0436	0.187
	(0.0277)	(0.0546)	(0.0328)	(0.0642)	(0.0430)	(0.0861)	(0.0443)	(0.0982)
No. Treated	2,190	1,242	1,559	945	986	695	885	752
	Productivity Distribution							
	1st		2nd		3rd		4th	
	ST	MT	ST	MT	ST	MT	ST	MT
Employment	0.0913***	0.283***	0.0579**	0.182***	0.0553***	0.260***	0.0442**	0.206***
	(0.0185)	(0.0375)	(0.0177)	(0.0384)	(0.0150)	(0.0389)	(0.0164)	(0.0333)
Turnover	0.113**	0.455***	0.0531*	0.127	0.0482	0.238***	0.0844**	0.177**
	(0.0492)	(0.0887)	(0.0259)	(0.0648)	(0.0303)	(0.0608)	(0.0309)	(0.0628)
No. Treated	1,359	823	1,342	824	1,382	912	1,526	1,061

Notes: Estimation based on Gateway to Research (GtR) and the Business Structure Database (BSD) for the period 2004-2016. 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. *** $p<0.001$, ** $p<0.01$, * $p<0.05$. The number of firms included in the treated group is reported. 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 refers to growth between t-1 and t+2, medium-term between t-1 and t+5.

Table 9: Impact of participation in innovation grants on firms' performance for single-grant and serial-grant holders

	No. Projects					
	Single Grant		**Serial Grant**		**Remove Outliers**	
	ST	MT	ST	MT	ST	MT
Employment	0.0585***	0.231***	0.0970***	0.306***	0.0602***	0.238***
	(0.00941)	(0.0205)	(0.0156)	(0.0299)	(0.00869)	(0.0191)
Turnover	0.0498*	0.200***	0.102**	0.380***	0.0562**	0.225***
	(0.0198)	(0.0400)	(0.0352)	(0.0579)	(0.0181)	(0.0353)
No. Treated	4,661	2,934	1,636	1,372	5,472	3,85

Notes: Estimation based on Gateway to Research (GtR) and the Business Structure Database (BSD) for the period 2004-2016. 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<0.001, ** p<0.01, * p<0.05. The number of firms included in the treated group is reported. Short-term refers to growth between t-1 and t+2, medium-term between t-1 and t+5.

Table 10: Impact of participation in innovation grants on firms' performance across distribution of project number of partners.

	No. Partner							
	1st		2nd		3rd		4th	
	ST	MT	ST	MT	ST	MT	ST	MT
Employment	0.0690***	0.250***	0.0734***	0.234***	0.0455**	0.222***	0.0598**	0.261***
	(0.0132)	(0.0370)	(0.0176)	(0.0378)	(0.0173)	(0.0332)	(0.0189)	(0.0347)
Turnover	0.0531	0.191**	0.0764*	0.275***	0.0287	0.253***	0.0817*	0.198**
	(0.0302)	(0.0717)	(0.0371)	(0.0684)	(0.0377)	(0.0641)	(0.0376)	(0.0695)
No. Treated	1,651	701	1,294	870	1,460	1,111	1,206	960

Notes: Estimation based on Gateway to Research (GtR) and the Business Structure Database (BSD) for the period 2004-2016. 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<0.001, ** p<0.01, * p<0.05. The number of firms included in the treated group is reported. Short-term refers to growth between t-1 and t+2, medium-term between t-1 and t+5.

Table 11: Impact of participation in innovation grants on firms' performance for projects with or without foreign partners and foreign leaders

	Foreign Partners		No Foreign Partners		Foreign Leader		No Foreign Leader	
	ST	MT	ST	MT	ST	MT	ST	MT
Employment	0.0523**	0.199***	0.0646***	0.258***	0.0433	0.173*	0.0627***	0.244***
	(0.0178)	(0.0345)	(0.00970)	(0.0216)	(0.0356)	(0.0679)	(0.00889)	(0.0193)
Turnover	0.0474	0.219**	0.0623**	0.237***	0.0384	0.370*	0.0598**	0.224***
	(0.0365)	(0.0681)	(0.0211)	(0.0418)	(0.0663)	(0.150)	(0.0192)	(0.0379)
No. Treated	1,432	1,077	4,200	2,565	333	202	5,299	3,440

Notes: Estimation based on Gateway to Research (GtR) and the Business Structure Database (BSD) for the period 2004-2016. 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<0.001, ** p<0.01, * p<0.05. The number of firms included in the treated group is reported. Short-term refers to growth between t-1 and t+2, medium-term between t-1 and t+5.

Table 12: Impact of participation in innovation grants on firms' performance across the distribution of firms' industrial closeness with other project partners.

	Partners Industrial Closeness							
	1st		2nd		3rd		4th	
	ST	MT	ST	MT	ST	MT	ST	MT
Employment	0.0607***	0.233***	0.0615***	0.241***	0.0696***	0.249***	0.0767***	0.280***
	(0.0104)	(0.0183)	(0.0111)	(0.0176)	(0.0108)	(0.0165)	(0.0120)	(0.0188)
Turnover	0.0473	0.166***	0.0599***	0.170***	0.0551**	0.194***	0.0728***	0.273***
	(0.0245)	(0.0209)	(0.0124)	(0.0211)	(0.0177)	(0.0293)	(0.0139)	(0.0250)
No. Treated	1,427	814	1,336	775	1,438	851	1,403	803

Notes: Estimation based on Gateway to Research (GtR) and the Business Structure Database (BSD) for the period 2004-2016. Industrial closeness estimated following the Neffke et al. (2011) methodology using relatedness between each pair of sectors based on co-occurrence analysis by Jaffe (1989). 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<0.001, ** p<0.01, * p<0.05. The number of firms included in the treated group is reported. Short-term refers to growth between t-1 and t+2, medium-term between t-1 and t+5.

Table 13: Impact of participation in publicly-funded projects awarded by EPSRC, Innovate UK, MCR and all the remaining UK research councils

	EPSRC		Innovate UK		MRC		Others	
	ST	MT	ST	MT	ST	MT	ST	MT
Employment	0.0741***	0.243***	0.0621***	0.235***	0.0484	0.269***	0.0231	0.225***
	(0.0211)	(0.0417)	(0.00977)	(0.0217)	(0.0480)	(0.0849)	(0.0297)	(0.0636)
Turnover	0.0858	0.269**	0.0606**	0.218***	0.164	0.281*	-0.0542	0.185
	(0.0454)	(0.0956)	(0.0207)	(0.0402)	(0.113)	(0.137)	(0.0576)	(0.111)
No. Treated	921	715	4,152	2,465	197	170	428	292

Notes: Estimation based on Gateway to Research (GtR) and the Business Structure Database (BSD) for the period 2004-2016. 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<0.001, ** p<0.01, * p<0.05. The number of firms included in the treated group is reported. Short-term refers to growth between t-1 and t+2, medium-term between t-1 and t+5.

Table 14: Impact of participation in publicly-funded projects awarded by EPSRC and Innovate UK across firms' size distribution

	EPSRC							
	Micro		***Small***		***Medium***		***Large***	
	ST	MT	ST	MT	ST	MT	ST	MT
Employment	0.121***	0.441***	0.106*	0.329***	0.0586	0.280**	-0.0222	0.121
	(0.0365)	(0.0671)	(0.0432)	(0.0801)	(0.0490)	(0.102)	(0.0501)	(0.0986)
Turnover	0.160	0.385*	0.249**	0.385*	0.116	0.264	0.0477	0.112
	(0.0918)	(0.184)	(0.0836)	(0.159)	(0.0852)	(0.172)	(0.0919)	(0.230)
No. Treated	219	160	215	170	229	172	256	211
	Innovate UK							
	Micro		***Small***		***Medium***		***Large***	
	ST	MT	ST	MT	ST	MT	ST	MT
Employment	0.0915***	0.232***	0.0632***	0.230***	0.0139	0.200***	0.0402	0.150*
	(0.0124)	(0.0279)	(0.0171)	(0.0388)	(0.0272)	(0.0578)	(0.0344)	(0.0639)
Turnover	0.0630*	0.203***	0.0680	0.211**	0.0707	0.242*	0.0527	0.184*
	(0.0294)	(0.0598)	(0.0368)	(0.0738)	(0.0527)	(0.102)	(0.0525)	(0.0896)
No. Treated	1,847	985	1,214	675	632	420	449	379

Notes: Estimation based on Gateway to Research (GtR) and the Business Structure Database (BSD) for the period 2004-2016. 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<0.001, ** p<0.01, * p<0.05. The number of firms included in the treated group is reported. Short-term refers to growth between t-1 and t+2, medium-term between t-1 and t+5. 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).

Table 15: Impact of participation in publicly-funded projects awarded by Innovate UK and collaborations with universities

	No University Partner		University Partner	
	ST	MT	ST	MT
Employment	0.0428*	0.202***	0.0706***	0.257***
	(0.0188)	(0.0361)	(0.0108)	(0.0267)
Turnover	0.106**	0.243***	0.0388	0.201***
	(0.0378)	(0.0684)	(0.0237)	(0.0486)
No. Treated	1,367	986	2,807	1,479

Notes: Estimation based on Gateway to Research (GtR) and the Business Structure Database (BSD) for the period 2004-2016 for UK firms participating to Innovate UK funded projects. 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<0.001, ** p<0.01, * p<0.05. The number of firms included in the treated group is reported. Short-term refers to growth between t-1 and t+2, medium-term between t-1 and t+5.

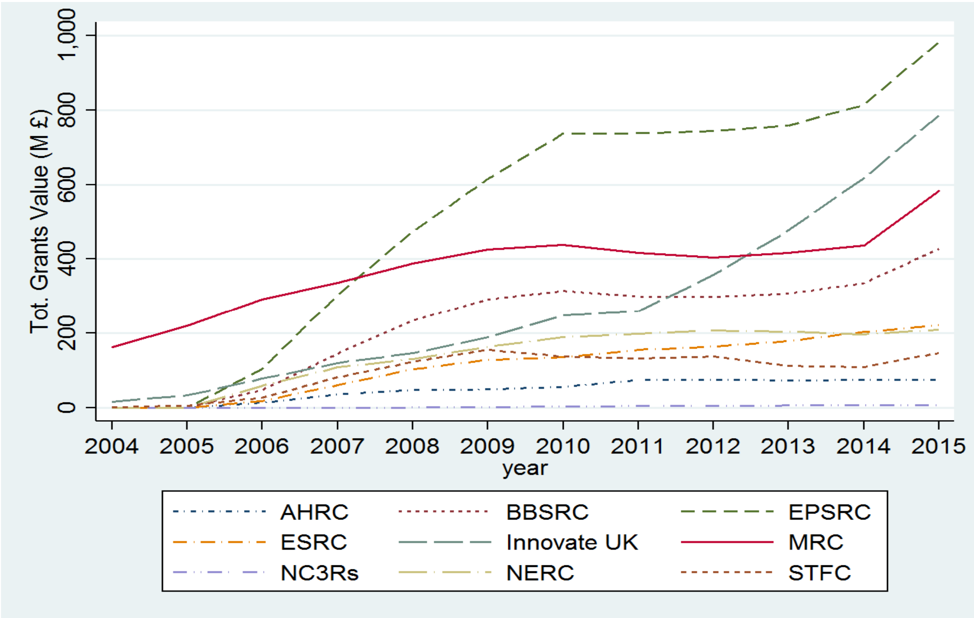
Table 16: Impact of participation in publicly-funded projects awarded by Innovate UK for SMEs before and after RDA termination in 2012.

	Innovate UK SME post-RDA									
	Treated - Untreated				*SMEs pre-post 2012 (Treated)*		*SMEs v Non-SMEs (Treated)*			
	SMEs Pre2012		*SMEs Post2012*				*Pre 2012*		*Post 2012*	
	ST	MT	ST	MT	ST	MT	ST	MT	ST	MT
Employment	0.0721***	0.111*	0.0620***	0.0759**	0.00757	-0.0201	-0.0900	-0.14314	0.204***	0.258**
	(0.0169)	(0.0446)	(0.0118)	(0.0244)	(0.0160)	(0.0418)	(0.0859)	(0.1104)	(0.0526)	(0.0867)
Turnover	0.237***	0.299***	0.153***	0.0388	0.0270	-0.0596	-0.0785	-0.210	0.180**	0.0650
	(0.0281)	(0.0613)	(0.0331)	(0.0623)	(0.0430)	(0.0805)	(0.0855)	(0.152)	(0.0924)	(0.176)
No. Treated	1,423	1,380	2,268	715	3,691	2,095	1,078	1,055	1,616	249

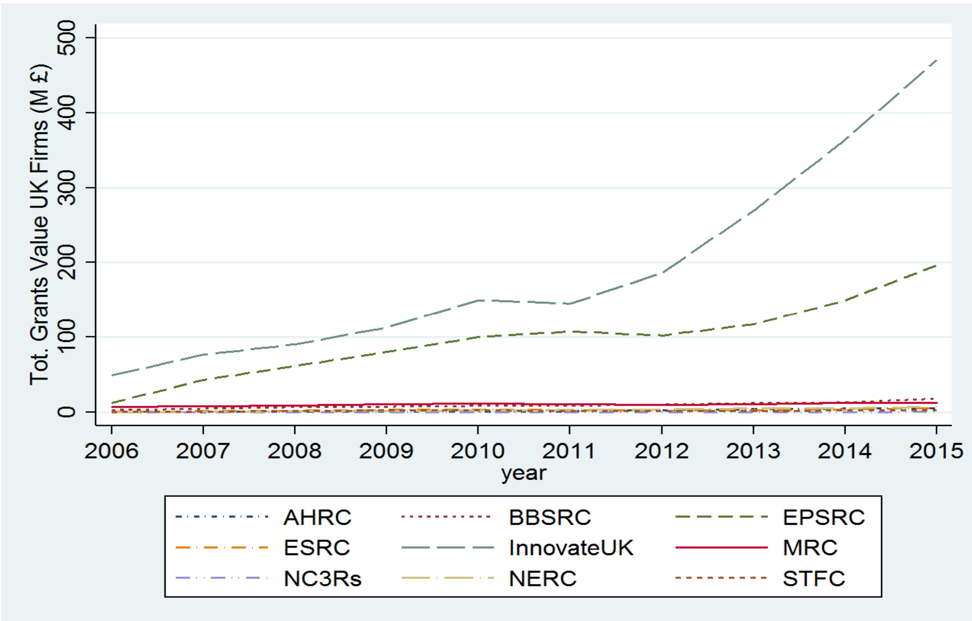
Notes: Estimation based on Gateway to Research (GtR) and the Business Structure Database (BSD) for the period 2004-2016 for UK firms participating to Innovate UK funded projects. ATT effect estimated using a difference-in-differences technique with propensity score nearest-neighbour matching procedure. Abadie and Imbens (2011) standard errors (s.e.) reported in parentheses. *** p<0.001, ** p<0.01, * p<0.05. The number of firms included in the treated group is reported. Short-term refers to growth between t-1 and t+2, medium-term between t-1 and t+5.

Figure 1: Total grants value per Research Council – all organizations and private firms only

(a) All organisations



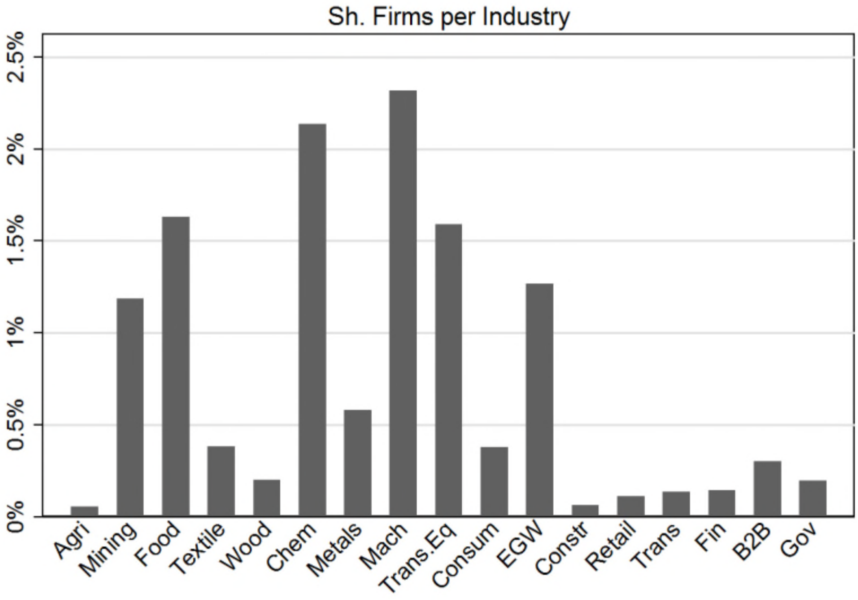
(b) Private firms only



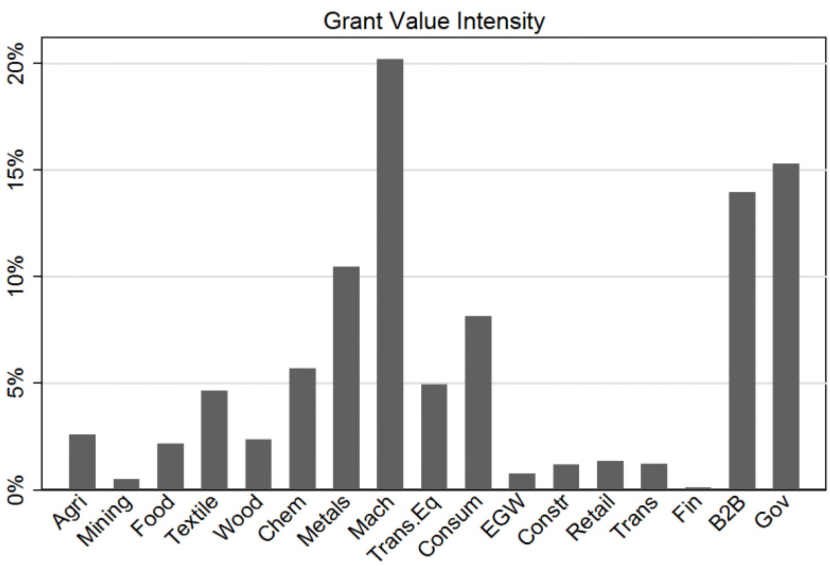
Notes: Statistics based on Gateway to research (GtR) data for the period 2004-2016. Grants value reported in millions of pounds.

Figure 2: Industrial distribution of treated firms and their grants intensity

(a) Treated firms by industry (%)

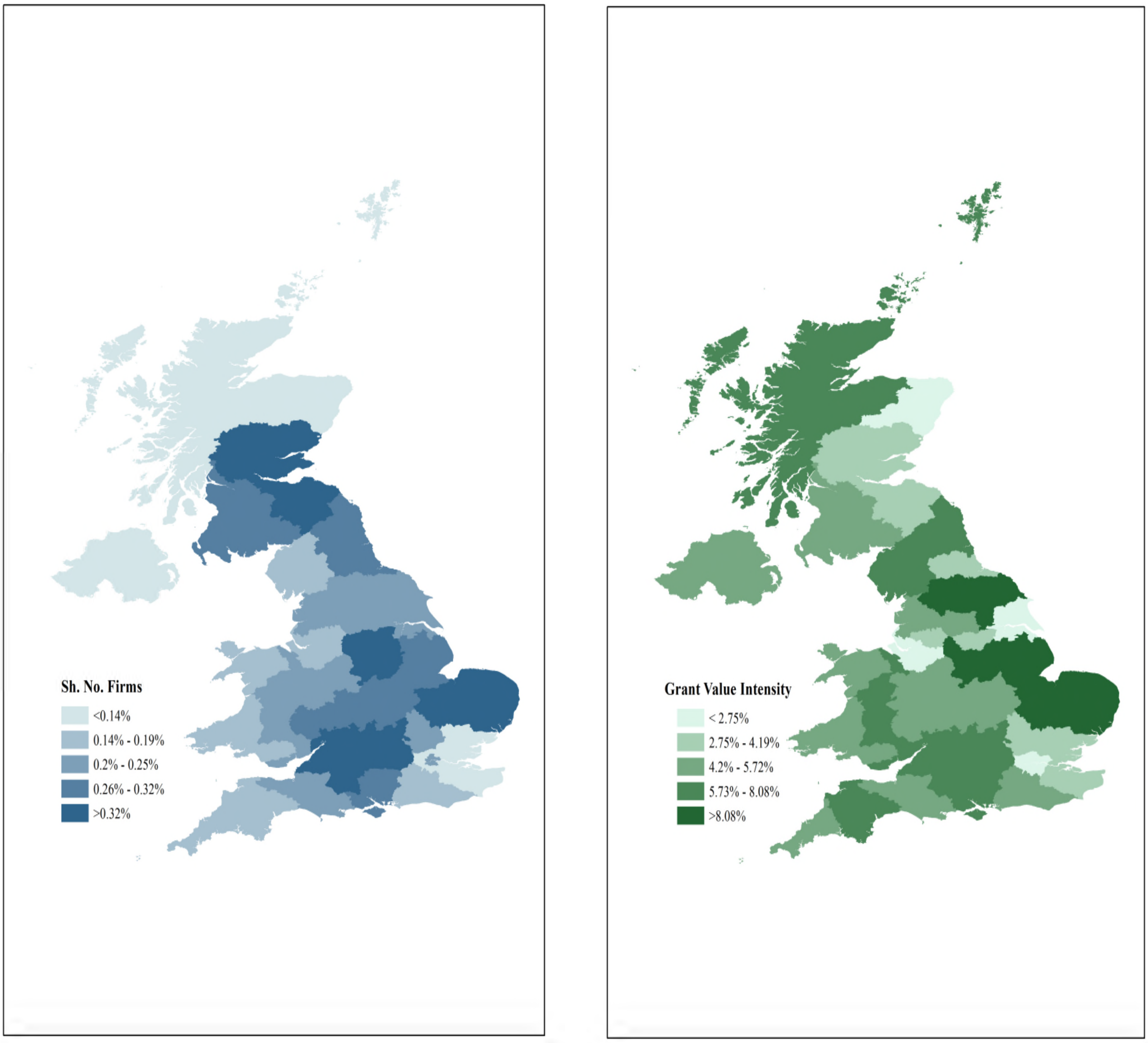


(b) Grant intensity by industry (% turnover)



Notes: Statistics based on Gateway to Research (GtR) and the Business Structure Database (BSD) for the period 2004-2016. Share of firms calculated as the ratio between the number of participating firms over the total number of firms in the industry at the SIC 2-digit level. Grant value intensity measured as the average value of grants awarded per year over the industry total turnover.

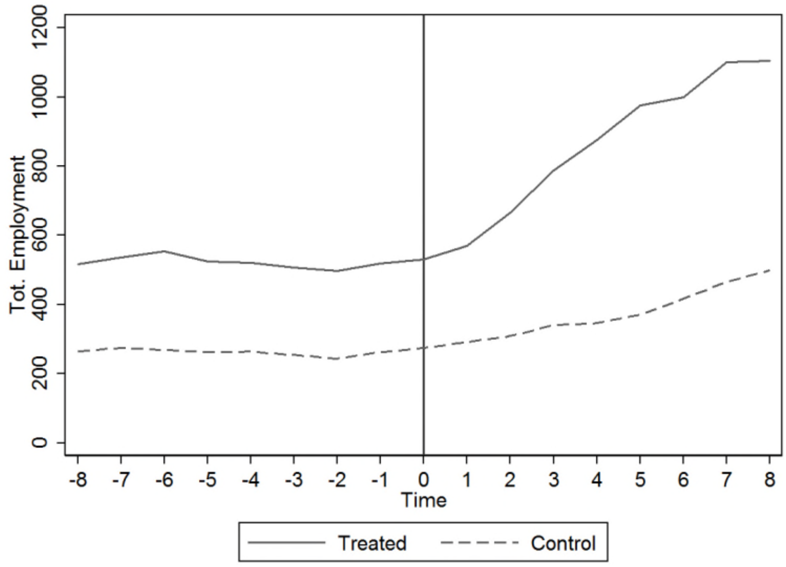
Figure 3: Regional distribution of treated firms and their grants intensity.



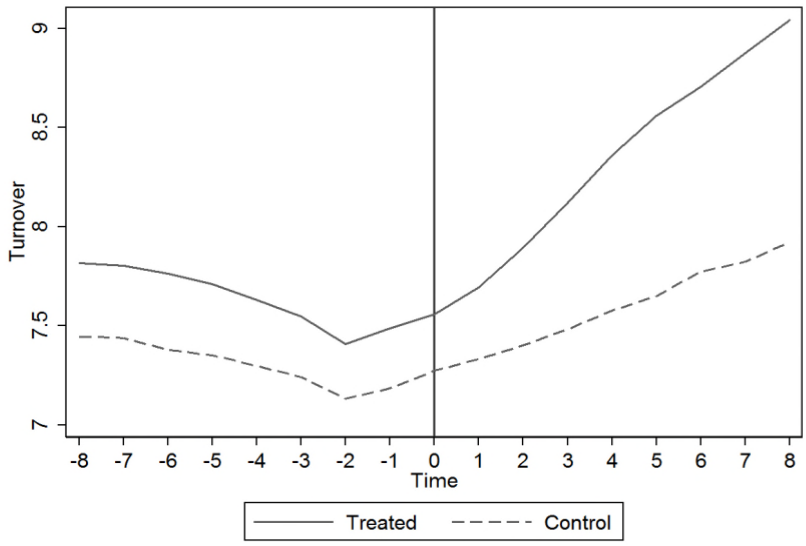
Notes: Statistics based on Gateway to Research (GtR) and the Business Structure Database (BSD) for the period 2004-2016. Share of firms calculated as the ratio between the number of participating firms over the total number of firms in the region at the NUTS 2-digit level. Grant value intensity measured as the average value of grants awarded per year over the regional total turnover.

Figure 4: Employment and turnover trends for treated and untreated firms before and after the beginning of the UKRC funded projects (t=0)

(a) Employment growth

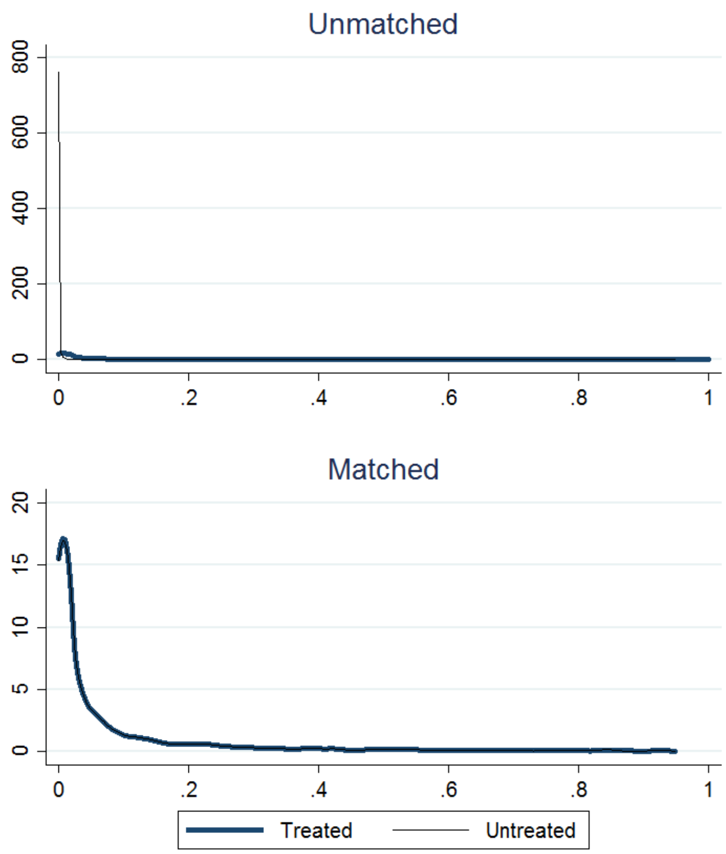


(b) Turnover growth



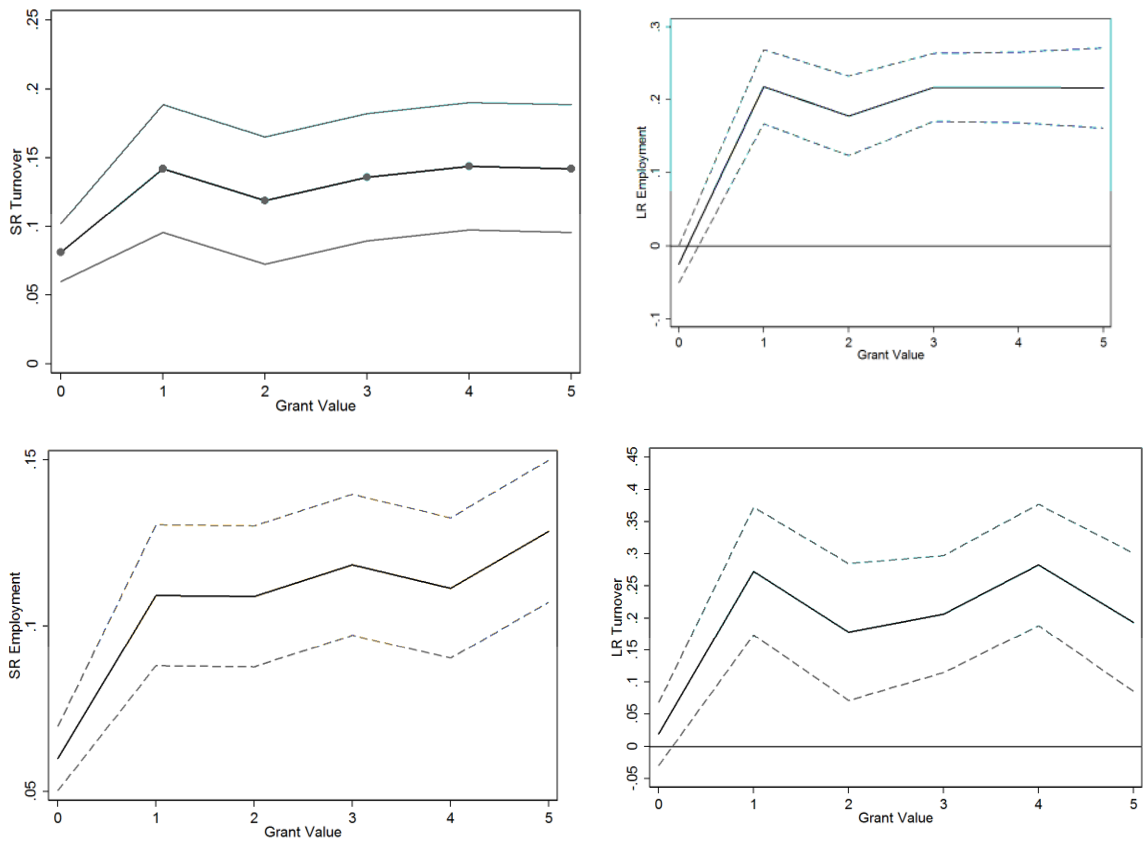
Notes: Statistics based on Gateway to Research (GtR) and the Business Structure Database (BSD) for the period 2004-2016. Average value of employment and turnover for treated observations reported up to 8 years before and after the treatment year t=0 and the median year in the sample for untreated observations.

Figure 5: Density distribution of propensity score for firms in the treated and control groups before and after the nearest-neighbour matching.



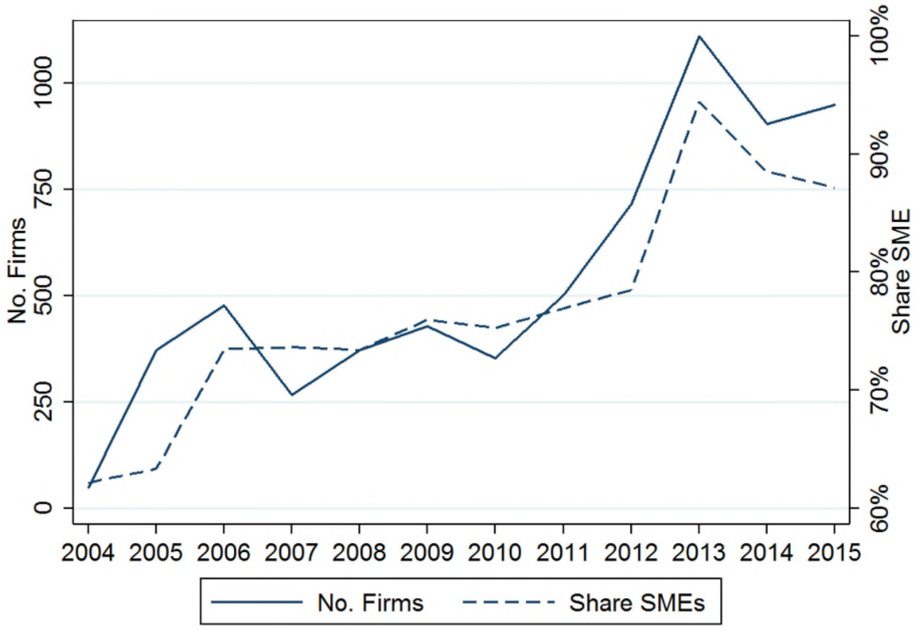
Notes: Estimation of the propensity score based on Gateway to Research (GtR) and the Business Structure Database (BSD) for the period 2004-2016 for UK based private firms using a logit model with one year lagged control variables.

Figure 6: Continuous treatment effect of grants value on firms' performance



Notes: Estimation based on Gateway to Research (GtR) and the Business Structure Database (BSD) for the period 2004-2016. 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<0.001, ** p<0.01, * p<0.05. The number of firms included in the treated group is reported. Short-term refers to growth between t-1 and t+2, medium-term between t-1 and t+5.

Figure 7: Trend in the number of firms and the share of SMEs supported by Innovate UK (minimum in 2004=74)



Notes: Statistics based on Gateway to Research (GtR) and the Business Structure Database (BSD) for the period 2004-2016 for UK firms participating to Innovate UK funded projects. Share of SMEs calculated as the number of SMEs (less than 250 employees) over the total number of firms funded by Innovate UK.

REFERENCES

Abadie, A. and Imbens, G. 2011. Bias-corrected matching estimators for average treatment effects. *Journal of Business & Economic Statistics* 29:1-11.

Aguiar, L. and Gagnepain, P. 2017. European co-operative R&D and firm performance: Evidence based on funding differences in key actions. *International Journal of Industrial Organization* 53:1-31.

Astebro, T. and Michela, J.L. 2005. Predictors of the survival of innovations. *Journal of Product Innovation Management* 22:322-335.

Barajas, A.; E. Huergo; and L. Moreno 2012. Measuring the economic impact of research joint ventures supported by the EU Framework Programme. *Journal of Technology Transfer* 37:917-942.

Bayona-Sáez, C. and Garcia-Marco, T. 2010. Assessing the effectiveness of the Eureka Program. *Research Policy* 39:1375-1386.

Becker, B. 2015. Public R&D policies and private R&D investment: A survey of the empirical evidence. *Journal of Economic Surveys* 29:917-942.

Becker B., Roper S., Love J. 2016. The effectiveness of regional, national and EU support for innovation in the UK and Spain. ERC Research Paper No 52.

Becker, S. and Ichino, A. 2002. Estimation of average treatment effects based on propensity scores, *Stata Journal* 2:358-377.

Bédu, N. and Vanderstocken, A. 2015. The effects of regional R&D subsidies on innovative SME: Evidence from Aquitaine SMEs. Cahiers du GREThA, Groupe de Recherche en Economie Théorique et Appliquée.

Belderbos, R., Carree, M. and Lokshin, B. 2004. Cooperative R&D and firm performance. *Research Policy* 33:1477-1492.

Bellucci, A., Pennacchio, L. and Zazzaro, A. 2016. Public subsidies for SME research and development: empirical evaluation of collaborative versus individual place–based programs. MOFIR Working paper no. 133.

Beugelsdijck, P.J. and Cornet, M. 2001. How far do they reach? The localisation of industrial and academic spillovers in the Netherlands. Centre discussion paper: 47.

Bryce, D. and Winter, S. 2009. A general inter-industry relatedness index. *Management Science* 55: 1570–1585.

Cabrales, A.L., Medina, C.C., Lavado, A.C. and Cabrera, R.V. 2008. Managing functional diversity, risk taking and incentives for teams to achieve radical innovations. *R & D Management* 38:35-50.

Calantone, R.J., Harmancioglu, N. and Droge, C. 2010. Inconclusive innovation "returns": A meta-analysis of research on innovation in new product development. *Journal of Product Innovation Management* 27:1065-1081.

Caliendo, M. and Kopeinig, S. 2008. Some practical guidance for the implementation of propensity score matching. *Journal of Economic Surveys* 22:31–72.

Cin, B.C., Kim, Y.J. and Vonortas, N.S. 2017. The impact of public R&D subsidy on small firm productivity: evidence from Korean SMEs. *Small Business Economics* 48:345-360.

Clausen, T.H. 2009. Do subsidies have positive impacts on R&D and innovation activities at the firm level? *Structural Change and Economic Dynamics* 20: 239-253.

Colombo, M.G., Croce, A. and Guerini, M. 2013. The effect of public subsidies on firms' investment-cash flow sensitivity: Transient or persistent? *Research Policy* 42: 1605-1623.

Colombo, M.G., Giannangeli, S. and Grilli, L. 2012. Public subsidies and the employment growth of high-tech start-ups: assessing the impact of selective and automatic support schemes. *Industrial and Corporate Change* 22: 1273-1314.

Criscuolo C., Martin R., Overman H.G. and Van Reenen J. 2016. The causal effects of an industrial policy. CEP Discussion Paper No 1113.

Czarnitzki, D. and Delanote, J. 2013. Young innovative companies: the new high-growth firms? *Industrial and Corporate Change* 22: 1315-1340.

Czarnitzki, D. and Lopes-Bento, C. 2014. Innovation subsidies: Does the funding source matter for innovation intensity and performance? Empirical evidence from Germany. *Industry and Innovation* 21:380-409.

Czarnitzki, D. and Lopes-Bento, C. 2013. Value for money? New microeconometric evidence on public R&D grants in Flanders. *Research Policy* 42:76-89.

De Blasio, G., Fantino, D., and Pellegrini, G. 2015. Evaluating the impact of innovation incentives: evidence from an unexpected shortage of funds. *Industrial and Corpoprate Change* 24:1285–1314.

Department for Business, Innovation and Skills, Office for National Statistics. 2018. UK Innovation Survey, 1994-2016: Secure Access. 6th Edition. UK Data Service. SN: 6699, http://doi.org/10.5255/UKDA-SN-6699-6.

D'Este, P., Guy, F. and Iammarino S. 2013. Shaping the formation of university–industry research collaborations: what type of proximity does really matter? *Journal of Economic Geography* 13(4): 537–558.

Dimos, C. and Pugh, G. 2016. The effectiveness of R&D subsidies: A meta-regression analysis of the evaluation literature. *Research Policy* 45:797-815.

Doh, S. and Kim, B. 2014. Government support for SME innovations in the regional industries: The case of government financial support program in South Korea. *Research Policy* 43:1557-1569.

Drach, A. 2017. Structural Change and the developemnt of business expenditure and R&D in Austria. Vienna: AIT and TU Wien.

Du, J.S., Leten, B., Vanhaverbeke, W. and Lopez-Vega, H. 2014. When research meets development: Antecedents and implications of transfer speed. *Journal of Product Innovation Management* 31:1181-1198.

Duch, N., Montolio, D. and Mediavilla, M. 2009. Evaluating the impact of public subsidies on a firm's performance: a two-stage quasi-experimental approach. *Investigaciones Regionales* 16:143-165.

Duguet, E. 2004. Are R & D subsidies a substitute or a complement to privately funded R & D? Evidence from France using propensity score methods for non-experimental data. *Revue d'Economie Politique* 114:263–292.

EC-DG ENTR 2009. *European competitiveness report*. Luxembourg.

Ellison, G. and Glaeser, E. 1997. Geographic concentration in U.S. manufacturing industries: A dartboard approach. *Journal of Political Economy* 105:889-927.

Engineering and Physical Sciences Research Council. 2015. EPSRC Annual report and accounts 2014-15. London.

Feldman, M. P. and Kelley, M.R. 2003. Leveraging research and development: Assessing the impact of the U.S. Advanced Technology Program. *Small Business Economics* 20:153-165.

Foreman-Peck, J. 2013. Effectiveness and efficiency of SME innovation policy. *Small Business Economics* 41:55-70.

Fosfuri, A. and Giarratana, M.S. 2009. Masters of war: Rivals' product innovation and new advertising in mature product markets. *Management Science* 55:181-191.

Frontier Economics. 2017. The impact of public support for innovation on firm outcomes. In *Research Paper*. London: Department of Business, Energy, Innovation and Skills.

Gonzalez, X., Jaumandreu, J. and Paz, O.C. 2005. Barriers to innovation and subsidy effectiveness. *The Rand Journal of Economics* 36:930–950.

Görg, H. and Strobl, E. 2007. The effect of R&D subsidies on private R&D. *Economica* 74:215–234.

Greene, F.J., 2009. Assessing the impact of policy interventions: the influence of evaluation methodology. *Environmental Planning C: Government Policy* 27:216–229.

Grimpe, C. and Kaiser, U. 2010. Balancing internal and external knowledge acquisition: The gains and pains from R&D outsourcing. *Journal of Management Studies* 47:1483-509.

Heckman, J., Ichimura, H. and Todd, P.E. 1997. Matching As an econometric evaluation estimator: Evidence from evaluating a job training programme. *Review of Economic Studies* 64:605-654.

Hewitt-Dundas, N., Gkypali, A. and Roper, S. 2017. Accessibility, utility and learning effects in university-business collaboration. ERC Research Paper No 57.

Hidalgo, C. A., Klinger, B., Barabási, A. L., and Hausmann, R. 2007. The product space conditions the development of nations. *Science* 317(5837): 482-487.

Hildreth, P. and D. Bailey. 2013. The economics behind the move to 'localism' in England. *Cambridge Journal of Regions Economy and Society* **6:233-249**.

Hottenrott, H., Lopes-Bento, C. and Veugelers, R. 2017. Direct and cross scheme effects in a research and development subsidy program. *Research Policy* 46: 1118-1132.

Hottenrott, H. and Lopes-Bento, C. 2016. R&D partnerships and innovation performance: Can there be too much of a good thing? *Journal of Product Innovation Management* 33:773-794.

Hottenrott, H. and Lopes-Bento, C. 2014. International R&D collaboration and SMEs: The effectiveness of targeted public R&D support schemes. *Research Policy* 43:1055-1066.

Howell, S.T. 2017. Financing innovation: Evidence from R&D grants. *American Economic Review* 107:1136-64.

Innovate UK. 2016. Innovate UK Delivery Plan Financial Year 2016/17. London: Innovate UK.

Jaffe, A. 1989. Real Effects of Academic Research. *American Economic Review* 79(5): 957-70.

Jaffe, A. 2013. An economic perspective on science and innovation policy. In: Working Paper, Motu Economic and Public Policy Research, Presented at the Economic Analysis of Industry and Innovation Programs Design Workshop. Australian National University, 20 September 2013.

Karhunen, H., & Huovari, J. 2015. R&D subsidies and productivity in SMEs. *Small Business Economics*, 45:805-823.

Keizer, J.A. and Halman, J.I.M. 2007. Diagnosing risk in radical innovation projects. *Research-Technology Management* 50:30-36.

Kilponen, J. and Santavirta, T. 2007. When do R&D subsidies boost innovation? Revisiting the inverted U-shape. Bank of Finland Research Discussion Paper No. 10/2007.

Klette, T.J., Moen, J. and Griliches, Z. 2000. Do subsidies to commercial R&D reduce market failures? Microeconomic evaluation studies. *Research Policy* 29: 471–495.

Laursen, K. and Salter, A. 2006. Open for innovation: the role of openness in explaining innovation performance among U.K. manufacturing firms. *Strategic Management Journal* 27:131–150.

Lechner, M. 2002. Program heterogeneity and propensity score matching: An application to the evaluation of active labor market policies. *The Review of Economics and Statistics* 84:205-220.

Lee, S. 2015. Slack and innovation: Investigating the relationship in Korea. *Journal of Business Research* 68:1895-1905.

Leiponen, A. and Byma, J. 2009. If you cannot block, you better run: Small firms, cooperative innovation, and appropriation strategies. *Research Policy* 38:1478-1488.

Lerner J. 1999. The government as venture capitalist: The long-run effects of the SBIR program. *Journal of Business* 72:285-318.

Leuven, E. and Sianesi, B. 2017. PSMATCH2: Stata module to perform full Mahalanobis and propensity score matching, common support graphing, and covariate imbalance testing.

Lhuillery, S. and Pfister, E. 2009. R&D cooperation and failures in innovation projects: Empirical evidence from French CIS data. *Research Policy* 38(1): 45-57.

Löfsten H. and Lindelöf P. 2002. Science Parks and the growth of new technology-based firms—academic-industry links, innovation and markets. *Research Policy* 31(6): 859-876.

Lokshin, B., Hagedoorn, J. and Letterie, W. 2011. The bumpy road of technology partnerships: Understanding causes and consequences of partnership mal-functioning. *Research Policy* 40:297–308.

Love, J.H., Roper, S., and Bryson, J.R. 2011. Openness, knowledge, innovation and growth in UK business services. *Research policy* 40:1438-1452.

Marlin, D. and Geiger, S.W. 2015. A reexamination of the organizational slack and innovation relationship. *Journal of Business Research* 68:2683-2690.

Martin, B.R. 2012. The evolution of science policy and innovation studies. *Research Policy* 41:1219-1239.

Mazzucato, M. 2016. From market fixing to market-creating: a new framework for innovation policy. *Industry and Innovation* 23:140-156.

Mechlin, G.F. and Berg, D. 1980. Evaluating research - ROI is not enough. *Harvard Business Review*: 93-99.

Menon, A., Chowdhury, J. and Lukas, B.A. 2002. Antecedents and outcomes of new product development speed - An interdisciplinary conceptual framework. *Industrial Marketing Management* 31:317-328.

Miotti, L. and Sachwald, F. 2003. Co-operative R&D: why and with whom? An integrated framework of analysis. *Research Policy* 32(8): 1481-1499.

Morandi, V. 2013. The management of industry–university joint research projects: how do partners coordinate and control R&D activities? *The Journal of Technology Transfer* 38(2): 69-92.

NESTA 2012. Compendium of evidence on the effectiveness of innovation policy. Manchester Institute of Innovation Research.

Neffke, F., Henning, M. and Boschma, R. 2011. How do regions diversify over time? Industry relatedness and the development of new growth paths in regions. *Economic Geography* 87: 237–265.

Nohria, N. and Gulati, R. 1996. Is slack good or bad for innovation? *Academy of Management Journal* 39:1245-1264.

OECD 2010. Innovation vouchers, ed. O.I.P. Platform. Paris: OECD.

Okamuro, H. 2007. Determinants of successful R&D cooperation in Japanese small businesses: The impact of organizational and contractual characteristics. *Research Policy* 36(10): 1529-1544.

Office for National Statistics. 2017. Business Structure Database, 1997-2017: Secure Access. 9th Edition. UK Data Service. SN: 6697, http://doi.org/10.5255/UKDA-SN-6697-9.

Palmer, T.B. and Wiseman, R.M. 1999. Decoupling risk taking from income stream uncertainty: A holistic model of risk. *Strategic Management Journal* 20:1037-1062.

Petruzzelli, A.M. 2011. The impact of technological relatedness, prior ties, and geographical distance on university–industry collaborations: A joint-patent analysis. *Technovation* 31:309-319.

Pearce, G. and S. Ayres. 2009. Governance in the English Regions: The Role of the Regional Development Agencies. *Urban Studies* **46:537-557**.

Pike, A.; M. Coombes; P. O'Brien; and J. Tomaney. 2018. Austerity states, institutional dismantling and the governance of sub-national economic development: the demise of the regional development agencies in England. *Territory Politics Governance* **6:118-144**.

Porter, M.E. and Van de Linde, C. 1995. Toward a new conception of the environment-competitiveness relationship. *Journal of Economic Perspectives* 9:97-118.

Rantisi, N. M. 2002, The competitive foundations of localized learning and innovation: The case of women's garment production in New York City. *Economic Geography*, 78:441–462.

Roper, S.; J. Du; and J.H. Love. 2008. Modelling the innovation value chain. *Research Policy* 37:961-977.

Roper, S.; J.H. Love; and K. Bonner. 2017. Firms' knowledge search and local knowledge externalities in innovation performance. *Research Policy* **46:43-56**.

Rosenbaum, P.R. and Rubin, D.B. 1983. The central role of the propensity score in observational studies for causal effects. *Biometrika* 70:41–55.

Rubin, D.B. 1977. Assignment to treatment group on the basis of covariate. *Journal of Educational Statistics* 2:1-26.

Scandura, A. 2016. University–industry collaboration and firms' R&D effort. *Research Policy* 45:1907-1922.

Sakakibara, M. 2001. The Diversity of R&D Consortia and Firm Behavior: Evidence from Japanese Data. *The Journal of Industrial Economics* 49: 181-196.

Siegel, D. S., Westhead P. and Wright M. 2003. Assessing the impact of university science parks on research productivity: exploratory firm-level evidence from the United Kingdom. *International Journal of Industrial Organization* 21(9): 1357-1369.

Technology Strategy Board. 2015. TSB (Innovate UK) Annual Report and Accounts 2014-15. London.

Teece, D. J., R. Rumelt, G. Dosi and S. Winter. 1994. Understanding Corporate Coherence. Theory and Evidence. *Journal of Economic Behavior and Organization* 23: 1-30.

Van Alphen, K.; Van Ruijven, J., Kasa, S., Hekkert, M. and Turkenburg, W. 2009. The performance of the Norwegian carbon dioxide, capture and storage innovation system. *Energy Policy* 37:43-55.

Vásquez-Urriago A.R., Barge-Gil A. and Modrego Rico A. 2016. Science and Technology Parks and cooperation for innovation: Empirical evidence from Spain. *Research Policy* 45: 137-147.

Von Beers, C. and Zand, F. 2014. R&D Cooperation, Partner Diversity, and Innovation Performance. *Journal of Product Innovation Management* 31: 292-312.

Von Ehrlich, M. and Seidel, T. 2015. The persistent effects of placed-based policy - Evidence from the West-German Zonenrandgebiet. ERSA conference papers, European Regional Science Association.

Von Raesfeld, A., Geurts, P., Jansen, M., Boshuizen, J. and Luttge, R. 2012. Influence of partner diversity on collaborative public R&D project outcomes: A study of application and commercialization of nanotechnologies in the Netherlands. *Technovation* 32(3–4):
227-233.

Von Stamm, B. 2003. *Innovation, Creativity and Design*. Chichester: John Wiley and Sons.

Wallsten, Scott J. 2000. The effects of government-industry R&D programs on private R&D: The case of the Small Business Innovation Research Program. *RAND Journal of Economics* 31:82-100.

Wang, Y., Li, J. and Furman, J.L. 2017. Firm performance and state innovation funding: Evidence from China's Innofund program. *Research Policy*, 46:1142-1161.

Woerter, M. and Roper, S. 2010. Openness and innovation--Home and export demand effects on manufacturing innovation: Panel data evidence for Ireland and Switzerland. *Research Policy* 39:155-164.

Yang C-H., Motohashi K. and Chen J-R. 2009. Are new technology-based firms located on science parks really more innovative? Evidence from Taiwan. *Research Policy* 38: 77-85.

Zehavi, A. and Breznitz, D. 2017. Distribution sensitive innovation policies: Conceptualization and empirical examples. *Research Policy* 46:327-336.

Zhao, B. and Ziedonis, R.H. 2012. State governments as financiers of technology startups: Implications for firm performance. Available at http://dx.doi.org/10.2139/ssrn.2060739.

Zona, F. 2012. Corporate investing as a response to economic downturn: Prospect theory, the behavioural agency model and the role of financial slack. *British Journal of Management* 23:S42-S57.

Zuniga-Vicente, J.A.; C. Alonso-Borrego; F.J. Forcadell; and J.I. Galan. 2014. Assessing the effect of public subsidies on firm R&D investment: A survey. *Journal of Economic Surveys* 28:36-67.

Table A1: Recent studies on the effect of public R&D subsidies to individual firms on business performance

Study / Estimation Methodology	Type of subsidy	Data	Sample period	Measure(s) of performance	Conclusions: Statistically significant effect on firm performance
BAYONA-SAEZ, GARCIA-MARCO (2010) *First-differences GMM, two-step estimator with corrected standard errors*	Eureka programme (EU)	Eureka programme database; Amadeus database by Bureau Van Dijk	1994-2003	Return over assets (ROA)	Positive (one year after project completion for manufacturing firms, during year of completion for non-manufacturing firms)
ZHAO, ZIEDONIS (2014) *Regression discontinuity design (among others)*	Direct R&D awards from the Michigan Life Science Corridor (MLSC), renamed Michigan Technology Tri-corridor (MTTC), then both subsumed under 21st Century Jobs Fund (21CJF) (consecutive Michigan state innovation programmes, US technology startups)	Michigan Economic Development Corporation (MEDC) for applicant-level data; Michigan Department of Licensing and Regulatory Affairs database for commercial viability data, VenturXpert for follow-on VC financing, SBIR awardee lists for SBIR awards, Delphion for successful applications of U.S. patents.	2002-2008	Survival (commercial viability) Receipt of follow-on venture capital financing	Positive Positive (for firms lacking prior VC-backing or Small Business Administration (SBA) awards; no significant effect otherwise
DE BLASIO, FANTINO, PELLEGRINI (2015) *Regression continuity design*	Fund for Technological Innovation (Italian firms), providing funding for projects that focus on the development component of R&D	Ministry for Economic Development archive for the programme; Cerved data sets of financial statements; patent applications data from the European Patent Office.	2001-2007	Sales (in logs) Financial conditions (long-term debt / assets, cash flow / assets) Assets (in logs)	No significant effect No significant effects Positive No significant effect

				Return over assets (ROA)	
KARHUNEN, HUOVARI (2015) *Combined matching and difference-in-differences*	Public R&D funds granted by Tekes, one of the agencies of the Ministry of Employment and the Economy (Finnish SMEs)	Business Register and Financial Statement databases for firm level data; patent database for patents applied for in Finland and in Europe and patents granted in the US; Concern database for information on whether a firm belongs to larger group; Statistics on Business Subsidies database (all Statistics Finland databases); Employee Characteristics database created from the Finnish Longitudinal Employer–Employee Data (FLEED) by Statistics Finland	2002-2012	Labour productivity (value added / number of FT employees, in logs) Employment Survival	No significant effect in the five-year period after a subsidy is granted, Negative one to two years after the subsidy year Positive Positive
CRISCUOLO, MARTIN, OVERMAN, VAN REENEN (2016) *Firm level regressions: various (OLS, reduced form, first stage, instrumental variables)*	Regional Selective Assistance Programme (RSA) (UK geographical areas at different levels; plant level; firm level)	Selective Assistance Management Information System (SAMIS) database for information on programme applicants; the Interdepartmental Business Register (IDBR) for the construction of jobs variables; unemployment data from the local areas labour market statistics through the ONS Nomis service; Annual Respondents Database (ARD) from the Annual Business Inquiry (ABI) for information on firms' investment, wages, productivity	1997-2004	Employment (manufacturing, in logs) Capital investment (in logs) Output (in logs) Total Factor Productivity (in logs)	Positive (small firms only) Positive Positive No significant effect
CIN, KIM, VONORTAS (2017) *Difference-in-differences*	Government R&D subsidy programme (Korean SMEs)	Annual Report of the Financial Statement of firms and public subsidy data; National Information and Credit Evaluation (NICE) for financial firm data; Small and Medium	2000-2007	Value-added productivity (value added / number of employees, in logs)	Positive

		Business Administration (SMBA) for data on government R&D subsidy			
HOWELL (2017) *Regression discontinuity design OLS, zero-inflated negative binomial panel regressions*	Government Department of Energy's (DOE) Small business innovation research (SBIR) programme (US firms) (grants awarded in two phases, about two years apart)	Data from the DOE offices of Fossil Energy and of Energy Efficiency and Renewable Energy; patents data from Berkeley's Fung Institute; metropolitan statistical area level data from the Federal Reserve Economic Data research centre.	1995-2013	Venture capital or angel investment received by firm after the grant competition's award Revenue (in logs)	Phase 1 grant: Positive sign. effect; Phase 2 grant: No Positive sign. effect; No
WANG, LI, FURMAN (2017) *Linear probability models* *Regression discontinuity design*	Innofund programme (Chinese firms) (Evidence of bureaucratic intervention in award process, in that applicants' evaluation scores are non-randomly missing and that some firms with scores below funding standards did receive grants)	Innofund programme data on grant applications and project ratings; patent applications from China's State Intellectual Property Office (SIPO); data on firm survival and ownership structure from the Beijing Administration of Industry and Commerce (BAIC).	2005-2010	Firm survival (exit measure: firm death by 2015) Equity investment received from venture capital or private equity firm by 2015	No significant effect No significant effect

Table A2: Recent studies on the effect of public R&D subsidies for R&D collaboration on business performance.

Study / Estimation Methodology	Type of subsidy	Data	Sample period	Measure(s) of performance	Conclusions: Statistically significant effect on firm performance
BARAJAS, HUERGO, MORENO (2012) *Recursive four equation model (step 1 ML Probit with sample selection (eqs. 1&2); steps 2 & 3 OLS random effects model, using predicted value from respective previous step)*	International research joint ventures supported by the EU Framework Programme (FP) (Spanish firms)	Centre for the Development of Industrial Technology (CDTI) database for information on all EU FP funding proposals, whether eventually granted or not; combined with SABI database for information on firms, e.g. employment.	1995-2005	[Intangible fixed assets per employee (in logs, to capture firms' technological capacity)] Labour productivity (sales per employee, in logs)	[Positive] Indirect positive effect via technological capacity
SCANDURA (2016) *Propensity score matching*	Engineering and Physical Science Research Council (EPSRC) grants awarded to university-industry (U-I) collaborations (UK firms)	Dataset on EPSRC U-I partnerships, collected by funding agency; combined with Office for National Statistics' (ONS) Business Structure Database (BSD) for information on firms, e.g. employment, location; and the ONS' Business Expenditure on R&D (BERD) database, for information on firms' R&D employment	1997-2007	Firm's share of R&D employment	Positive (two years after the end of the collaboration project)
AGUIAR, GAGNEPAIN (2017) *Two-step (step 1 Logit, step 2 OLS and IV)*	Industry-oriented research joint ventures supported by the EU Framework Programme (FP), specifically the 'user-friendly information	Community Research and Development Information Service (CORDIS) for information on the IST projects; AMADEUS from Bureau van Dijk for information on firms	1998-2002	Labour productivity (value added per employee) Profit margin (profit before tax as a ratio to operating revenue)	Positive No significant effect

	society' (IST) sub-programme (EU firms)				
BELLUCCI, PENNACCHIO, ZAZZARO (2018) *Difference-in-differences propensity score matching*	Regional research and innovation subsidies for collaborative research projects between SMEs and universities (Italian firms)	Data on regional programme collected by Marche Innovazione, the regional development agency for innovation, together with Department of Information Engineering (DIIGA) of Univ. Polytechnic of Marche, Ancona; AIDA from Bureau van Dijk for accounting data on subsidized and non-subsidized firms; REGPAT from OECD for information on patent applications to the European Patent Office at the regional level	2003-2012	Firm's sales Firms' profitability (return on equity)	No significant effect Negative in short term, positive in medium term

Table A3: Definitions of main variables included in the analysis

Name	***Description***
Employment	Total number of full-time employees (BSD).
Employment Squared	Squared total number of employees (BSD).
Turnover	Total sales generated by the firm in a year (BSD).
Labour Productivity	Ratio of turnover per employee (BSD).
Age	Number of years since the birth of the firm (BSD).
Pre-treatment Employment Growth	Employment growth in the 2-years period before the award of the project (BSD).
Pre-treatment Labour Productivity Growth	Productivity growth in the 2-years period before the award of the project (BSD).
Group	Dummy variable equal to 1 if firm is part of a business group (BSD).
Foreign Owned	Dummy variable equal to 1 if firm is owned by a foreign company (BSD).
Market Share	Share of firm total sales over industry total sales at the national level (SIC 4-digit level) (BSD).
Single Plant	Dummy variable equal to 1 if firm is composed of a single plant (BSD).
Total Patents	Cumulative number of patents owned by the firm since 1980 (UK IPO).
Science Park	Dummy variable equal to 1 if firm is located in the same postcode district of a science park (UKSPA).
Peer Effect	Number of firms supported by UKRCs over total number of firms within the same region-industry (GtR and BSD)
.Agglomeration Index	Ellison and Glaeser (1997) index of region-industry agglomeration measured as the difference between the squared share of employment of an industry in a given region and the squared share of employment of a region in the country, divided by the squared share of employment of the industry in the country, divided by the Herfindhal Index of industrial concentration (BSD).
Region-industry R&D Intensity	Region-industry R&D intensity measured as the ration between total expenditure in R&D and total turnover (UKIS).
Competition Index	Total number of firms operating within the same region and industry (BSD).
Region-Industry Labour Productivity	Average labour productivity at the region-industry level (BSD).
Region-Industry Employment	Total employment at the region-industry level (BSD).
Industry	SIC 2003 classification at 4-digit level (BSD).
Region	Local Enterprise Partnerships boundaries for England and NUTS 2-digit level boundaries for Wales, Scotland and Northern-Ireland (BSD).
Manufacturing Industries	Dummy variable equal to 1 for all firms in the SIC (2003) sectors between code 15 and code 37 (BSD).
Services Industries	Dummy variable equal to 1 for all firms in the SIC (2003) sectors between code 40 and code 95 (BSD).
High-Tech Industries	Dummy variable equal to 1 for firms in the SIC (2003) manufacturing sectors 24, 29, 30, 31, 32, 33, 34 and 35 (BSD).
Knowledge Intensive Services	Dummy variable equal to 1 for firms in the SIC (2003) services sectors 61, 62, 64, 65, 66, 67, 70, 71, 72, 73, 74, 80, 85 and 92 (BSD).

Industrial Closeness	Industrial relatedness between each pair of sectors s and j is estimated using co-occurrence analysis through a cosine index (Jaffe, 1989). Industrial closeness is measured using indicator function taking the value 1 if the relatedness between the firm and each other partner in the project is above the mean or not and taking the ratio of close relations over the total number of possible relations in the project is calculated (BSD).
Short-term Growth	Average employment or turnover growth between time t-1 and t+2 (BSD).
Medium-term Growth	Average employment or turnover growth between time t-1 and t+5 (BSD).
Firm size distribution	Firms are categorised 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) (BSD).

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