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Knowledge to money: Assessing the business performance effects of publicly-funded R&D 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 UKRCs over the 2004–2016 period and applying a 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 medium term. 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, 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.

1. 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 programmes 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 2004–2016 period as well as the characteristics of the partners involved in each research project. Of particular importance in terms of business engagement within 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 the GtR data with the Business Structure Database, which provides longitudinal data on the performance of all UK firms in terms of employment and turnover growth. This allows us to assess the impacts on business growth of participating in UKRC funded projects but also to explore how growth impacts vary depending on firm characteristics, project participants and the particular Research Council providing finance.

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[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.

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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 academics and governmental institutions (OECD[2] ; 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 and firms. Secondly, exploiting the richness of the data provided by the GtR portal, we provide novel insights into how the characteristics of individual projects and the characteristics of project partners influence their returns. Do projects with more participants, international participants or university partners generate greater returns? How do returns differ depending on whether projects are UK-led or led by international 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 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 (RDAs) in 2012.

We employ a propensity score matching technique to analyse the differences in performance growth between firms who participated in RC-funded projects and a matched comparator group of firms which received no support based on their probability of participation. 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 although as expected this effect varies depending on the nature of the participating firm, the characteristics of project participants and the funder.

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.

2. Conceptual framework

Public support for private R&D is generally justified in terms either of market failures linked to firms' difficulty in appropriating the returns from R&D, or 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 et al., 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 et al., 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

[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, Behavioural & 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/.

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. 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 Lopes-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 programmes 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 Programmes 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 programme in Flanders, considering how these effects could vary over time, according to the different sources of funding and the cumulative and sequential impact of different supported projects for each single firm. The authors find a positive impact of public support on the creation of new R&D jobs, with a stable effect over time regardless of the subsidy's 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 programmes 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 A1).

The first papers in this field focused mostly on United States innovation and technology programmes, 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 Programmes 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, 2012; 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 programme of investment subsidies, find that areas eligible for public support create significantly more manufacturing jobs. However, this

[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 organisations 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).

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 programme, 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 programmes 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 programmes 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 (2013) 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 (see Table A2). 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 et al., 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 the costs of finding suitable partners, coordinating and managing research networks, possible leakage of innovation and technologies, free-riding and opportunistic behaviours (Grimpe and Kaiser, 2010; Lokshin et al., 2011; Hottenrott and Lopes-Bento, 2016; Bellucci et al., 2016).

In terms of the effects of collaborative subsidies 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

[7] However, the authors emphasise 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.

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 et al., 2011; Woerter and Roper, 2010; Rantisi, 2002; Petruzzelli, 2011; Laursen and Salter, 2006; Bellucci et al., 2016).

3. 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 1401 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, towards the end of our study period EPSRC had an annual budget of around £900 m which is used to fund research (c. £700 m) and training and fellowship grants (c. £200 m) (EPSRC, 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 organisations 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 other financial contributions by firms or other organisations. 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 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. 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 Fig. 1.[14] 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

[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).

[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.

[14] See Table A3 in the appendix for variable definitions.

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	5585	8.0%	742	2.3%
BBSRC	11,208	16.0%	3750	11.8%
EPSRC	15,528	22.1%	9270	29.1%
ESRC	5675	8.1%	1930	6.1%
Innovate UK	13,870	19.8%	4920	15.5%
MRC	7250	10.3%	7190	22.6%
NC3Rs	248	0.4%	49	0.2%
NERC	6963	9.9%	2430	7.6%
STFC	3851	5.5%	1530	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.

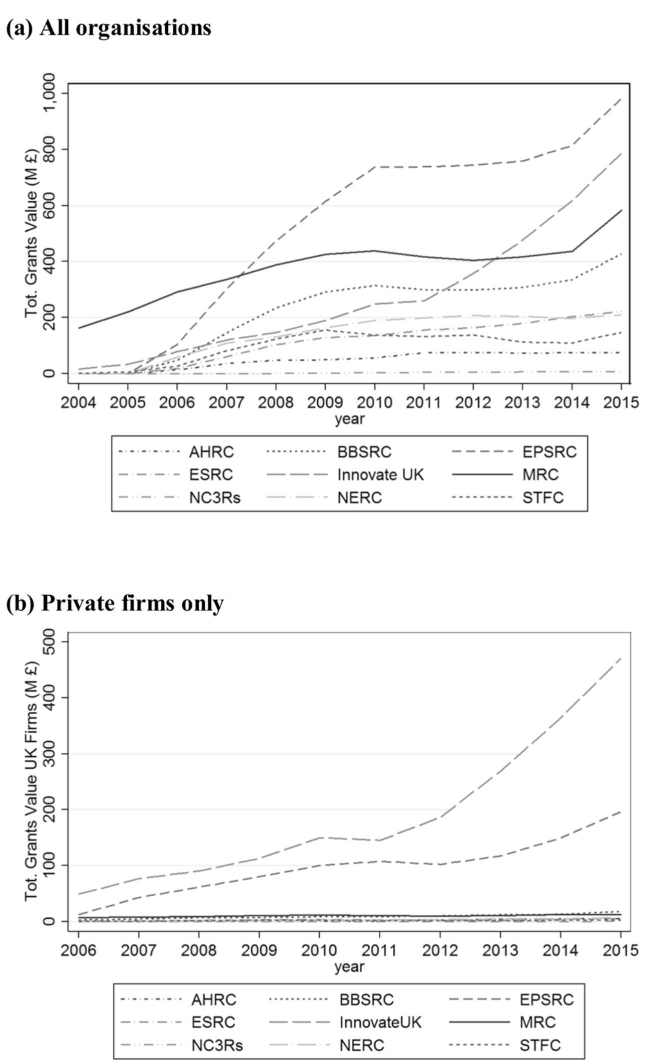


Fig. 1. Total grants value per Research Council – all organisations and private firms only.
Notes: Statistics based on Gateway to research (GtR) data for the period 2004–2016. Grants value reported in millions of pounds.

Table 2
Number and average value of projects funded by UK Research Councils by participants organisation type.

	Firms	Government	Universities	Pub.R&D Inst.	Priv.R&D Inst.
No. Organisations	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. Organisations	423	256	1680	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 organisation type; average grant value (£); average number of projects per organisation. Where projects are collaborative, project value is divided equally between participating organisations.

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 organisation. As shown in Table 2, we categorised the 34,000 participating organisations in 10 different categories: private firms, universities, public research institutes, private R&D centres, schools, hospitals, government authorities, charities, cultural organisations and others.[15] The largest group of organisations 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 the ONS Business Structure Database (BSD), accessed through the UK Data Service and covering the whole population of businesses in the UK between 1997 and 2016 (ONS, 2017).[16] 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.[17]

[15] We define as others academic journals, associations, funds, membership organisations and federations.

[16] 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.

[17] 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.

3.3. Methodology

3.3.1. Application of propensity score matching to the GtR Data

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 programme.

To overcome this issue we apply a propensity score matching (PSM) technique at the firm-level, as suggested in previous papers facing similar empirical challenges (Almus and Czarnitzki, 2003; Czarnitzki and Licht, 2006; Aerts and Schmidt, 2008; González and Pazó, 2008; Guerzoni and Raiteri, 2014; Scandura, 2016), creating a suitable control group of non-treated firms which is as similar as possible to the group of treated firms based on the likelihood of receiving the treatment (Caliendo and Kopeinig, 2008). By using a PSM technique we aim to control for the selection bias based on observable covariates by comparing treated with comparable untreated firms, while taking into account unobserved heterogeneity by comparing their differences in performance growth before and after the treatment (Heckman et al., 1997; Imbens, 2004).

Our identification strategy relies on comparing the performance of participating firms before and after their participation in publicly-funded projects compared to the performance 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 using a linear regression model as developed by Leuven and Sianesi (2017).

Firms in our sample may have received RC-funded grants in any year between 2006 and 2016, and although they may have participated to more than one project, we focus on the impact of the first project in order to better identify the causal effect of receiving public support while getting rid of other externalities and learning processes occurring during the implementation of a project (Scandura, 2016).[18] [19] Thus, we build a new time variable t set equal to 0 for the year in which firms participate in their first publicly-funded research project.[20] We then measure the average growth rate of the outcome variables y^1_{t+n}, employment and turnover,[21] as the difference between the pre-treatment log level at time *t-1* and the levels in the short-term (ST) 2 years after the treatment, and in the medium-term (MT) 5 years after the treatment.[22] 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}) in terms of performance growth after the start of the project at time $t+n$ 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 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; Lechner, 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 innovation activities.[23] 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).[24] 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,[25] the region-industry competition level measured with the net entry-exit rate, region-industry employment and turnover per employee levels, and finally year, region (LEP or NUTS 2-digit level) and industry (SIC 4-digit) dummies.

We estimate a separate propensity score for each sub-sample of interest (see below), in order to take into account the heterogeneous likelihood of being treated for firms with different characteristics. In Table 4 we report the propensity score estimation results for the general sample which is consistent with previous studies.[26] 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

[18] The GtR data start from 2004, while our analysis starts from 2006. We thus use the first two years of grants data to check if firms have been active in R&D grants before the beginning of our period of analysis. As a robustness test, we repeat the same analysis but starting from 2008, so using 4 years of GtR data to check the previous history of firms' participation in UKRC funded projects. The results reported in Table 5 are very similar and robust across the two specifications.

[19] As a robustness test, to relax the strong focus on the first grant and take into consideration the effect of all grants received on firms' performance, in Table 5 we also report the results of the analysis considering all grants received while controlling for previous grant participation in the propensity score estimation. The results are robust and consistent with our main specification.

[20] For untreated firms included in the control group *t=0* represents their median year in the sample.

[21] 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.

[22] 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.

[23] Data on firms' patents was provided by the UK Intellectual Property Office.

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

[25] 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.

[26] Results of the propensity score estimations for all the other sub-samples are similar and available upon request.

Table 3
Summary statistics of treated firms by category.

	General	Manufacturing	Services	HT	LT	KIS	Non-KIS
No. Firms	8943	2141	6802	1169	829	4309	2459
Tot. Value Grants (M £)	9000	1170	7820	968	1150	7180	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
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
Size	602	391	689	365	405	389	1550
Age	16	21	14	21	21	13	18
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.

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 and in a region-industry surrounded by other participants to RC projects also have 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 Calliper bandwidth, matching each treated observation only with the closest untreated observation within a 0.05 range in the propensity score. We restrict the matching to firms located in the same region at the LEP or NUTS 2–digit level and operating within the same sector at the SIC 4-digit level. In addition, since the balancing test between the treated and control group was not always completely satisfactory for some of the control variables after the matching, we have implemented a coarsened exact matching forcing the matching to be only between firms that are both inside (or outside) of a science park, and have similar values in terms of number of patents previously registered and of market share. 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 account the additional source of variability introduced by the estimation of the propensity score (Heckman et al., 1997).[27]

3.3.2. Results from our propensity score matching for the GtR data

After estimating the propensity score, dropping outliers and keeping only firms which satisfy the common support condition, our final sample contains almost 6000 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.[28] In addition, Figs. 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 ones are the machinery and professional services sectors. Geographically, the distribution in Fig. 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.

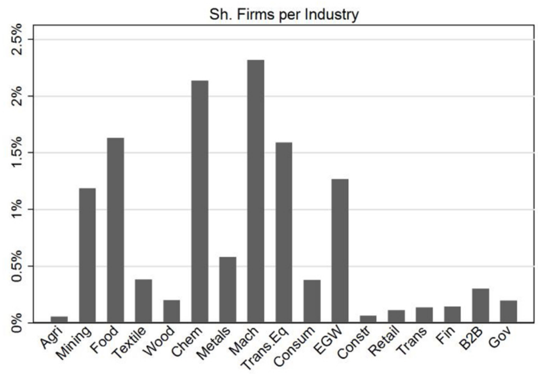
Table 4 reports the results of the balancing tests verifying the consistency of the construction of the control group and the overall quality of the matching procedure for the general sample of firms.[29] To check the propensity score balancing we report mean differences across the treated and control 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 not significant, 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 Fig. 4 which plots the time trends for the two main outcome variables for the pre-project and treatment periods for all firms in our

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

[28] 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.

[29] Balancing tests for all the other sub-samples of interest are similar and available upon request.

(a) Treated firms by industry (%)



(b) Grant intensity by industry (% turnover)

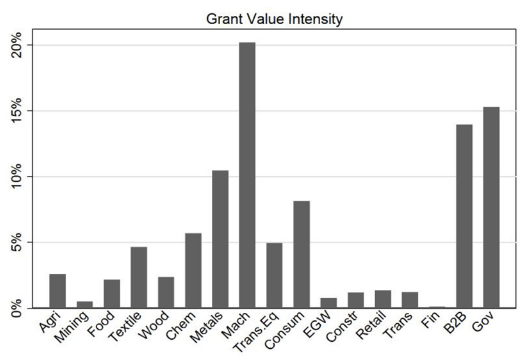


Fig. 2. Industrial distribution of treated firms and their grants intensity.
Notes: Statistics based on Gateway to Research (GtR) and the Business Structure Database (BSD) for the period 2004–2016. Share of firms calculated as the ratio between the number of participating firms over the total number of firms in the 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.

dataset. In the pre-project period, i.e. before the beginning of the UKRC funded projects at time $t = 0$, the outcome variables employment and turnover exhibit very similar trends to the group of untreated firms. Overall, 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).

Finally, we estimate a linear regression model following the Leuven and Sianesi (2017) methodology on a pooled cross-sectional dataset where for any given firm we observe the treatment dummy, the propensity score, the different control variables and the dependent variables of employment and turnover growth between period $t - 1$ and the short-term ($t + 2$) and the medium term ($t + 5$) periods. By matching based on the propensity score and controlling for year and industry fixed-effect, along with other control variables, we get a reliable estimate of the impact of receiving RC-funded grants on participating firms. However, it is important to bear in mind the limitations of this methodology. First, despite being widely adopted in innovation policy research because of its ability to deal with potential common support problems, propensity score matching does not fully reduce the concerns of unobservable factors explaining grant allocation and post-grant performances. Second, this methodology cannot establish the impact of the treatment beyond the eligible groups of treated and control observations included in the analysis, potentially biasing the estimation of the overall economic effect if these groups are not representative of the entire population.

4. 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 the characteristics of different RC-funded projects 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 firms' employment and turnover growth in our general sample, both in the short and medium-term. Employment grows on average 4.8% faster in treated firms in the 3 years following the award, and almost 21% in the medium-term.[30] Turnover growth is also positively affected by participation, increasing in the short-term by almost 7.6% and 23% in the medium-term. Overall, RC-funded firms create around 150 new jobs more than untreated firms in the control group 5 years after receiving publicly-funded R&D grants, while increasing their turnover by almost £45 million more than untreated firms over the same period. 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),[31] are robust to using a kernel matching technique instead of the Nearest-Neighbour method (columns 5 and 6) with very similar marginal effects, and have consistent statistical significance when considering not only first-time participants, but all RC-funded grants received by firms over this period (columns 7 and 8).

Secondly, in Table 6 we analyse potential sector-specific patterns, following the predictions of the conceptual framework, differentiating between manufacturing and services firms,[32] high-tech versus low-tech manufacturing firms, and between knowledge intensive services (KIS) and non-KIS companies. 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, the impact on turnover growth is greater for manufacturing companies, increasing by almost 31% in the medium-term, compared to only 19.5% in service firms. Differentiating between high-tech/low-tech manufacturing firms and between KIS and non-KIS companies, we find that the effects on employment are relatively similar for high-tech compared with low-tech manufacturing firms, while however the substantial effects on medium-term turnover growth,

[30] Note that sample sizes for the medium-term comparisons are smaller than those for the short-term comparisons as we do not have medium-term performance data for firms starting their project later in the sample period.

[31] 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.

[32] 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.

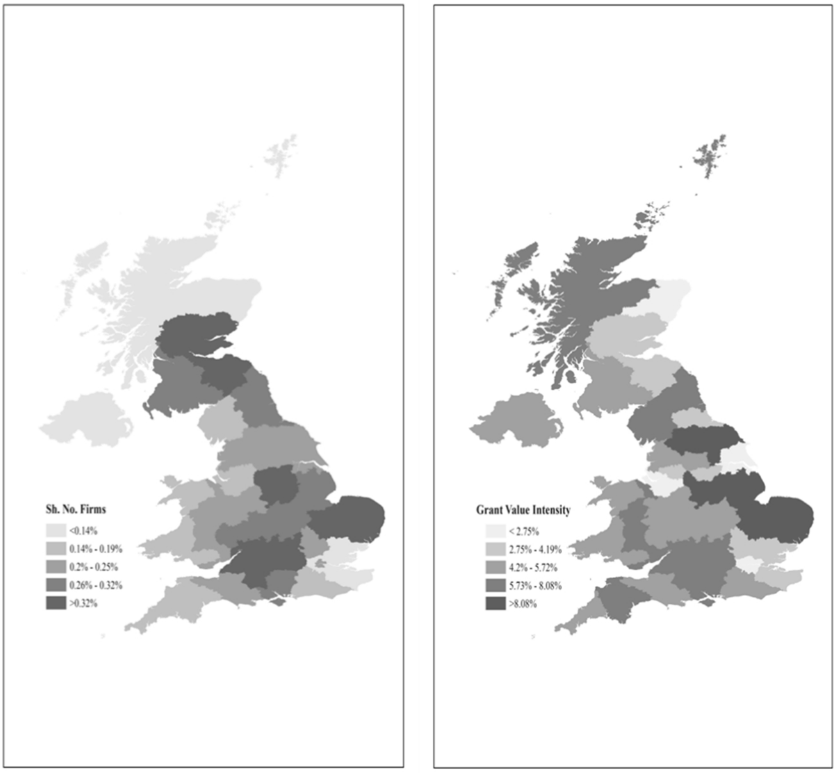


Fig. 3. Regional distribution of treated firms and their grants intensity.
Notes: Statistics based on Gateway to Research (GtR) and the Business Structure Database (BSD) for the period 2004–2016. Share of firms calculated as the ratio between the number of participating firms over the total number of 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.

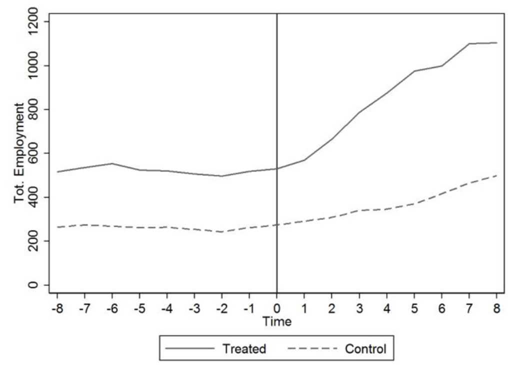
Table 4
Propensity Score estimation and matching average balancing test.

	Propensity Score		Mean		Bias	t-test		Var.
	coeff.	s.e.	Treated	Control	Perc.	t-value	p-value	Ratio
Employment	0.329***	(0.0048)	3.3542	3.3579	0.2	0.09	0.926	1.03
Lab. Prod.	−0.0072	(0.0063)	4.3083	4.2899	1.7	0.59	0.557	1.27
Age	−0.124***	(0.0093)	2.5405	2.5556	1.7	0.79	0.427	0.96
Empl. Growth	0.0183	(0.0229)	0.08357	0.08793	2	0.63	0.531	0.7
Lab. Prod. Growth	0.0246	(0.0165)	0.0299	0.03745	1.6	0.6	0.548	1.36
Group	0.178***	(0.0152)	0.35085	0.35511	1.1	0.33	0.738	.
Foreign Owned	−0.143***	(0.0226)	0.06641	0.06996	1.9	0.53	0.597	.
Science Park	0.217***	(0.0149)	0.16371	0.17259	2.7	0.89	0.373	.
Aggl. Index	1.178*	(0.666)	0.00631	0.00603	1.4	0.76	0.445	1
Reg. R&D Int.	0.0048	(0.0033)	8.9609	9.0199	2.7	1.01	0.313	0.99
Competition Index	0.306**	(0.151)	0.05595	0.05547	0.3	0.34	0.735	1.01
Reg-Ind. Lab. Prod.	−0.0324	(0.0227)	4.7163	4.7151	0.2	0.09	0.93	0.97
Reg-Ind. Empl.	−0.0976***	(0.0116)	9.8927	9.8784	0.9	0.33	0.744	1.05
Market Share	0.878***	(0.130)	0.01648	0.0151	2.8	0.68	0.494	1.04
Peer Effect	0.0008***	(0.0001)	54.404	55.589	1.1	0.74	0.457	0.88
Single Plant	0.0124	(0.0150)	0.47124	0.45597	3.4	1.15	0.251	.
Tot. Patents	0.275***	(0.0179)	0.09633	0.10144	1.6	0.35	0.729	0.68
R^2	*LR-chi^2*	*p.chi^2*	*Mean Bias*	*Med. Bias*	*B*	*R*	*Treated*	*Untreated*
0.001	6.69	0.987	1.7	1.6	6.9	0.86	5662	5662

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 standardised 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 is included.

almost 30%, are only experienced by high-tech firms. This latter result is similar to what might be anticipated on the basis of the previous literature (Love et al., 2011; Bellucci et al., 2016). Participating firms in KIS sectors benefit substantially more in terms of both short-term and medium-term employment compared with those in non-KIS sectors, 25% versus 11% in the medium term, for example, while here turnover growth effects are more balanced between the two groups of firms. Overall, these results suggest that participation in publicly-funded

(a) Employment growth



(b) Turnover growth

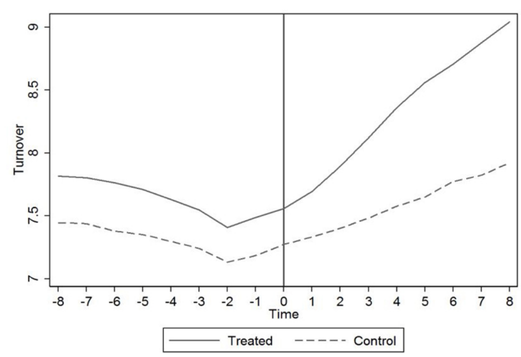


Fig. 4. Employment and turnover trends for treated and untreated firms before and after the beginning of the UKRC funded projects ($t = 0$).

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. The average standard deviation for employment for treated observations is equal to 217.28, for untreated observations 125.14. The average standard deviation for turnover for treated observations is equal to 1.426, for untreated observations 1.303.

Table 5

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

	General		After 2008		General - Kernel		All Grants	
	ST	MT	ST	MT	ST	MT	ST	MT
Employment	0.0483***	0.207***	0.0644***	0.231***	0.0642***	0.171***	0.0071***	0.0562***
	(0.0101)	(0.0196)	(0.00907)	(0.0206)	(0.0071)	(0.0121)	(0.0012)	(0.0112)
Turnover	0.0763***	0.231***	0.0569**	(0.0180)	0.0892***	0.252***	0.0098***	0.0431***
	(0.0182)	(0.0371)	0.221***	(0.0376)	(0.0173)	(0.0299)	(0.0002)	(0.0087)
No. Treated	5662	3668	4391	2425	5662	3668	18762	10,911

Notes: Estimation based on Gateway to Research (GtR) and the Business Structure Database (BSD) for the period 2004–2016. ATT effect estimated using a 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 $t + 5$.

research projects has a positive effect even on the performance of firms in sectors with low average R&D intensity, however only in the medium term.

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 growth of participating firms is significant regardless of the industry R&D intensity, with similar magnitudes across the four quartiles of the distribution, and similarly so for the medium-term effect across the region-industry distribution, while only the least R&D-intensive sectors record a short-term employment boost. However, we find evidence that the positive effect on turnover growth is much larger for firms operating in the most, compared with the least, R&D intensive regions and industries, increasing their total revenue due to RC support in the short-run by almost 22% and in the medium-term up to 32% (Table 7, Panel 2, 4th quartile). We also observe that regional peer effects are important for the least R&D intensive industries, in particular with regard to turnover

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	0.0379*	0.239***	0.0370*	0.205***	0.0140	0.212***
	(0.0176)	(0.0363)	(0.0179)	(0.0537)	(0.0290)	(0.0631)
Turnover	0.0607	0.306***	0.0670	0.229**	0.0412	0.182
	(0.0349)	(0.0616)	(0.0410)	(0.0748)	(0.0462)	(0.103)
No. Treated	1565	1103	923	677	622	411
	Services		KIS		Non-KIS	
	ST	MT	ST	MT	ST	MT
Employment	0.0518***	0.240***	0.0697***	0.253***	0.0329	0.114**
	(0.0104)	(0.0214)	(0.0121)	(0.0244)	(0.0204)	(0.0428)
Turnover	0.0416	0.195***	0.0664*	0.137**	0.0196	0.157*
	(0.0215)	(0.0430)	(0.0264)	(0.0506)	(0.0326)	(0.0631)
No. Treated	3984	2492	2880	1813	1094	670

Notes: Estimation based on Gateway to Research (GtR) and the Business Structure Database (BSD) for the period 2004–2016. ATT effect estimated using a 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 the distribution of region-industry R&D intensity (quartiles).

	Industry R&D Intensity							
	1 st		2nd		3rd		4th	
	ST	MT	ST	MT	ST	MT	ST	MT
Employment	0.0352*	0.190***	0.0613**	0.252***	0.0643**	0.312***	0.0722***	0.269***
	(0.0141)	(0.0324)	(0.0216)	(0.0572)	(0.0251)	(0.0497)	(0.0170)	(0.0367)
Turnover	0.00764	0.221	0.116*	0.299**	0.0268	0.201*	0.149***	0.302***
	(0.0308)	(0.123)	(0.0465)	(0.0931)	(0.0470)	(0.0800)	(0.0393)	(0.0695)
No. Treated	1964	1182	850	548	1013	658	1352	933
	Region-Industry Peer Effect							
	1st		2nd		3rd		4th	
	ST	MT	ST	MT	ST	MT	ST	MT
Employment	0.0512***	0.209***	0.0377	0.212***	0.0288	0.210***	0.00425	0.197**
	(0.0101)	(0.0239)	(0.0231)	(0.0446)	(0.0225)	(0.0494)	(0.0324)	(0.0681)
Turnover	0.0647**	0.187***	0.0121	0.258**	0.101*	0.238*	0.220***	0.322*
	(0.0220)	(0.0412)	(0.0388)	(0.0785)	(0.0478)	(0.0930)	(0.0655)	(0.156)
No. Treated	1447	1105	1461	903	1457	923	1248	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 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 $t+5$.

growth effects. 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, firms in R&D intensive sectors may be better able to capitalise on the results of the publicly-funded research in terms of total sales in the medium-term, highlighting the role of internal absorptive capacity in converting 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 firm 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 in Table 8.[33] It is evident that, as suggested by Becker (2015), smaller and

[33] In terms of scale, we grouped firms according to their initial level of employment at time *t-1*, categorising 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*.

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

	Scale Distribution							
	Micro		Small		Medium		Large	
	ST	MT	ST	MT	ST	MT	ST	MT
Employment	0.0822***	0.279***	0.0586***	0.254***	0.0676***	0.261***	0.0121	0.0820
	(0.0115)	(0.0249)	(0.0156)	(0.0338)	(0.0192)	(0.0429)	(0.0348)	(0.0561)
Turnover	0.0744**	0.228***	0.0902**	0.341***	0.0811*	0.282***	0.0739	0.164
	(0.0287)	(0.0577)	(0.0328)	(0.0644)	(0.0399)	(0.0783)	(0.0643)	(0.0898)
No. Treated	2191	1243	1559	945	986	696	864	731
	Productivity Distribution							
	1st		2nd		3rd		4th	
	ST	MT	ST	MT	ST	MT	ST	MT
Employment	0.0732***	0.302***	0.0275	0.177***	0.0455*	0.258***	0.0323	0.192***
	(0.0193)	(0.0392)	(0.0217)	(0.0430)	(0.0200)	(0.0501)	(0.0166)	(0.0324)
Turnover	0.143**	0.400***	0.0428	0.138*	0.0255	0.187*	0.00914	0.113
	(0.0497)	(0.0947)	(0.0305)	(0.0625)	(0.0373)	(0.0763)	(0.0398)	(0.0653)
No. Treated	1360	824	1344	827	1166	762	1539	1072

Notes: Estimation based on Gateway to Research (GtR) and the Business Structure Database (BSD) for the period 2004–2016. ATT effect estimated using a 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 participants.

	Single Grant		Serial Grant		Remove Outliers	
	ST	MT	ST	MT	ST	MT
Employment	0.0480***	0.198***	0.0846***	0.298***	0.0641***	0.201***
	(0.00930)	(0.0194)	(0.0165)	(0.0326)	(0.0215)	(0.097)
Turnover	0.0296	0.156***	0.134***	0.366***	0.0491**	0.188***
	(0.0188)	(0.0372)	(0.0358)	(0.0616)	(0.0232)	(0.0521)
No. Treated	4678	2948	1647	1337	5479	3581

Notes: Estimation based on Gateway to Research (GtR) and the Business Structure Database (BSD) for the period 2004–2016. ATT effect estimated using a 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 $t + 5$. Single Grant participants are firms which participated in only one project during the sample period either as leader or a project partner. Serial Grant participants participated in more than one project either as leader or a project partner.

less productive participating firms 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 30% faster than untreated firms and an increase in turnover by more than 40% (Table 8, Panel 2, 1st quartile). Instead there is almost no statistical difference in employment and turnover growth between treated and untreated large firms with more than 250 employees.

4.2. UKRC projects' heterogeneity

4.2.1. Number of projects, number of project partners and characteristics of project participants

We now focus on the effect of different project 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.

Table 10
Impact of participation in innovation grants on firms' performance across the distribution of project number of partners (quartiles).

	No. Partners Distribution							
	1st		2nd		3rd		4th	
	ST	MT	ST	MT	ST	MT	ST	MT
Employment	0.0476***	0.174***	0.0821***	0.225***	0.0458**	0.242***	0.0952***	0.269***
	(0.0143)	(0.0334)	(0.0168)	(0.0354)	(0.0160)	(0.0344)	(0.0189)	(0.0336)
Turnover	0.0401	0.0888	0.0715*	0.261***	0.0395	0.332***	0.143***	0.287***
	(0.0301)	(0.0684)	(0.0358)	(0.0660)	(0.0341)	(0.0636)	(0.0376)	(0.0669)
No. Treated	1648	700	1300	876	1469	1119	1213	964

Notes: Estimation based on Gateway to Research (GtR) and the Business Structure Database (BSD) for the period 2004–2016. ATT effect estimated using a 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 Leader		Domestic Leader		No Foreign Partners	
	ST	MT	ST	MT	ST	MT
Employment	0.0550	0.223**	0.0594***	0.229***	0.0480***	0.233***
	(0.0356)	(0.0724)	(0.00987)	(0.0188)	(0.00989)	(0.0213)
Turnover	0.148	0.398**	0.0782***	0.238***	0.0514*	0.209***
	(0.0583)	(0.134)	(0.0182)	(0.0362)	(0.0202)	(0.0412)
No. Treated	332	201	5237	3464	4212	2574
	Foreign Partners		**Foreign Firm Partner**		**Other Foreign Partner**	
	ST	MT	ST	MT	ST	MT
Employment	0.0500**	0.239***	0.0511**	0.188***	0.0452	0.332***
	(0.0181)	(0.0333)	(0.0219)	(0.0423)	(0.0314)	(0.0534)
Turnover	0.0596	0.315***	0.0740	0.316***	0.0337	0.336***
	(0.0320)	(0.0625)	(0.0404)	(0.0810)	(0.0578)	(0.0975)
No. Treated	1442	1086	906	647	508	419

Notes: Estimation based on Gateway to Research (GtR) and the Business Structure Database (BSD) for the period 2004–2016. ATT effect estimated using a 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 $t+5$.

First, in Table 9 we look at the number of RC-funded projects in which firms participated during our sample period, differentiating between single project participants, the majority of firms in our sample, and serial-project participants. Single-project participants are firms which participated – as either leader or partner – in only one project during the sample period. Serial project participants participated – as either leader or partner – in at least one additional project. As expected, we find a stronger positive impact for serial-project participants, increasing their size by almost 30% and their turnover by 36% 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 also highly significant for firms participating in only a single research project, except for short-term turnover growth. This highlights the benefits of publicly-funded R&D for firms not repeatedly involved in such 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. This could also lay the basis for more firms to form partnerships that may continue to provide benefits beyond the (initial) RC grant, and for these firms to potentially develop into 'serial' project participants themselves. In addition, in the last two columns of Table 9, we test the robustness of our results to outliers by removing from our general sample the firms in the top percentile of the number-of-projects distribution.[34] The results are similar to the estimations for the general sample presented in Table 5.

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 previous contributions, larger R&D projects could have a more positive impact on the performance of participating firms, mainly by increasing the opportunities for learning from partners, which could improve the R&D project output and subsequently firms' growth (Belderbos et al., 2004; Okamuro, 2007). However, too large a number of partners could also have a dampening impact on the outcome of the R&D collaboration, increasing uncertainty and the cost of coordination, monitoring and control (Morandi, 2013). Our results in Table 10 suggest that the number of partners in RC-funded projects is not relevant for the employment performance of participating firms, since the ATTs are always positive and statistically significant across the quartile distribution of the number of partners and not statistically different from each other. More partners seems to have some beneficial influence only on turnover growth.

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

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

	Partners Industrial Closeness							
	1st		2nd		3rd		4th	
	ST	MT	ST	MT	ST	MT	ST	MT
Employment	0.0386***	0.183***	0.0392***	0.193***	0.0563***	0.209***	0.0607***	0.229***
	(0.0117)	(0.0277)	(0.0113)	(0.0258)	(0.0119)	(0.0292)	(0.0115)	(0.0270)
Turnover	0.0349	0.116*	0.0396	0.187***	0.0601*	0.209***	0.0714**	0.239***
	(0.0232)	(0.0487)	(0.0240)	(0.0483)	(0.0244)	(0.0508)	(0.0236)	(0.0503)
No. Treated	1430	815	1341	777	1440	852	1405	805

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 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 $t+5$.

It could be argued that it is not the number of partners per se, but their characteristics which influence the performance of firms participating in 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 considers the ATTs in situations where firms participated in RC-funded projects together with foreign partners or only with domestic partners, and whether a domestic or a foreign partner was the project lead. It is well known from the international business literature, that foreign firms are typically more technologically advanced and exhibit higher productivity than domestic firms. Since most foreign partners in RC-funded projects during our sample period were firms, we might expect better performance from projects with foreign involvement. However, the increased complexity and cost of coordination in the interaction with foreign partners, especially when the leader of the project is geographically and organisationally distant from domestic participants, and from the providers of the R&D support, could combine to hold back performance (Miotti and Sachwald, 2003; Lhuillery and Pfister, 2009; D'Este et al., 2013).[35] About 25% of the treated firms in our sample participated in RC-funded projects that involved one or more foreign partners. The performance effect with regard to employment are relatively similar for domestic firms which collaborate with foreign partners compared with firms which collaborate with domestic partners only. However, medium-term turnover growth effects are larger from domestic-foreign collaborations, about 21% versus 31.5%. Interestingly, a similar difference in medium-term turnover growth performance can be observed between foreign-led versus domestic-led projects. In the short-term however, foreign-led projects seem to exert no performance benefits, while domestic-led projects increase employment and turnover growth by about 6% and 8%, respectively. So generally, with regard to turnover growth over a medium-term horizon, external knowledge introduced by foreign partners and leaders seems to be conducive to better performance for participating domestic firms.

4.2.2. Project partners' industry relatedness and projects' grant value

Related to the previous point, we next examine the potential importance of industry relatedness between project partners. We follow the methodology proposed by Neffke et al. (2011) and use spatial co-occurrence between sectors at the SIC 5-digit level as a measure of firms' industrial relatedness (Jaffe, 1989).[36] Table 12 shows that the positive impact of participation in RC-funded projects on employment, and particularly on turnover, growth is larger as firms' industrial relatedness with their project partners increases. For instance, the employment growth after 6 years from the beginning of the research project increases from 18% to 23% moving from the bottom to the top quartile of the industrial relatedness distribution, while from 11% to 24% in terms of turnover growth. Therefore, closer industrial relatedness between project partners improves the growth outcomes of research projects for firms. Industry coherence, rather than diversity, seems to magnify the positive effects of RC support (Sakakibara, 2001; Von Raesfeld et al., 2012; D'Este et al., 2013; Von Beers and Zand, 2014).

Finally, we contribute to the existing literature by considering the continuous treatment effect of RC grant value on firms' growth. Information about grant or subsidy value is often not available in innovation and R&D data sources, and so the impact of the amount of grant or subsidy support, compared with the question of whether or not support was received, remains under-researched. To do so, we follow the Hirano and Imbens (2005) methodology generalising the binary treatment propensity score approach for continuous treatment variables. First, we estimate a generalised propensity score focusing only on the sample of treated firms based on the amount of the grant received, using the same control variables employed in the binary treatment propensity score estimation.[37] After checking the adequacy of the propensity score estimation and the balance of all covariates across treatment intervals, we estimate the dose–response function, averaging

[35] If foreign partner involvement in a project were to increase exports and hence market size, this might also have a positive effect on performance (e.g. Peters et al., 2018). However, firms that collaborate only with domestic partners in RCUK-funded projects may of course also be exporters as part of their wider operations.

[36] 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 investigate 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, and thus create an indicator function that takes the value of 1 if the relatedness between the firm and each other partner in the project is above the mean, and a value of 0 otherwise. We then calculate the ratio of close relations over the total number of possible relations in the project.

[37] Results of the continuous propensity score estimation and of its balancing test are available upon request.

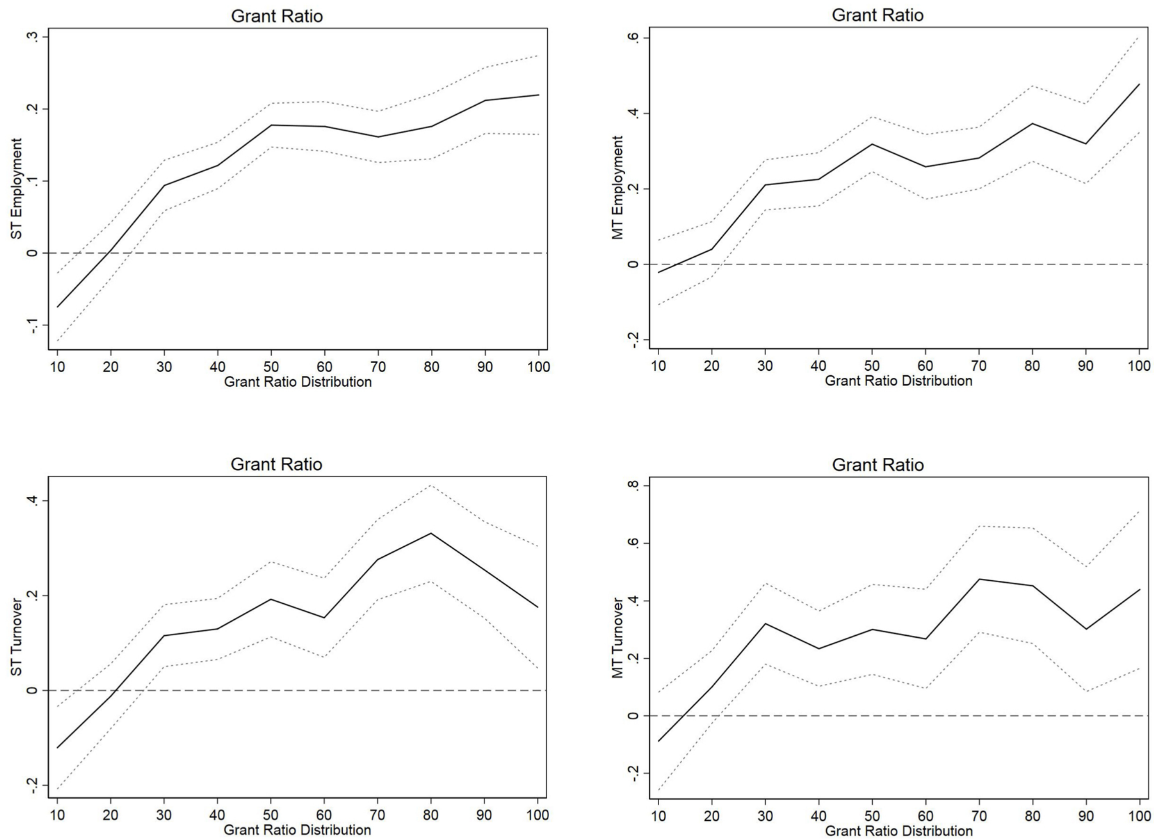


Fig. 5. Continuous treatment effect of grants value on firms' performance.
Notes: Estimation based on Gateway to Research (GtR) and the Business Structure Database (BSD) for the period 2004–2016. ATT effect estimated using a propensity score nearest-neighbour matching procedure at each decile of the grants rate distribution. Abadie and Imbens (2011). 95% Confidence intervals reported as dotted lines.. Short-term refers to growth between $t-1$ and $t+2$, medium-term between $t-1$ and $t+5$. Grant ratio is measured as grants total value over firms' turnover to take into account the size of the grant in respect to the size of the firm. The sample of treated firms included in the analysis is the same as in the general estimation sample in Table 5 (ST: 5662; MT: 3668).

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		Other RCs	
	ST	MT	ST	MT	ST	MT	ST	MT
Employment	0.0618**	0.242***	0.0437***	0.165***	0.0556	0.317***	0.0198	0.232***
	(0.0239)	(0.0428)	(0.0102)	(0.0204)	(0.0472)	(0.0748)	(0.0302)	(0.0568)
Turnover	0.163***	0.266***	0.0353*	0.175***	0.156	0.230	0.00653	0.179
	(0.0441)	(0.0741)	(0.0198)	(0.0388)	(0.117)	(0.170)	(0.0592)	(0.110)
No. Treated	931	723	4160	2471	199	172	426	291

Notes: Estimation based on Gateway to Research (GtR) and the Business Structure Database (BSD) for the period 2004–2016. ATT effect estimated using a 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 $t+5$.

the estimated regression function over the score function evaluated at different levels of the treatment. In this way, we are able to evaluate if the relative grant size, measured as the ratio between the grant value over total turnover before the treatment, has an impact on firms' employment and turnover growth.

In Fig. 5, we report the marginal effect for each decile of the grant ratio distribution, along with the 95% confidence intervals, finding a positive and significant effect of the relative size of grants on employment and turnover growth, with an average magnitude in line with the results estimated in our general sample. In particular, we find that

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	0.141***	0.440***	0.0630**	0.250**	0.0232	0.228*	0.00593	0.0388
	(0.0402)	(0.0659)	(0.0301)	(0.0894)	(0.0451)	(0.0955)	(0.0444)	(0.0867)
Turnover	0.248*	0.469**	0.249**	0.366*	0.0519	0.382*	0.0330	−0.110
	(0.0975)	(0.180)	(0.0866)	(0.152)	(0.0912)	(0.152)	(0.0784)	(0.141)
No. Treated	219	160	216	171	234	176	260	214
	Innovate UK							
	Micro		Small		Medium		Large	
	ST	MT	ST	MT	ST	MT	ST	MT
Employment	0.0782***	0.216***	0.0376*	0.230***	−0.0375	0.115*	−0.0125	0.168*
	(0.0121)	(0.0284)	(0.0167)	(0.0415)	(0.0340)	(0.0600)	(0.0449)	(0.0721)
Turnover	0.0516**	0.217***	0.0738*	0.281***	0.0124	0.0576	−0.0195	0.147
	(0.0287)	(0.0589)	(0.0331)	(0.0746)	(0.0460)	(0.0960)	(0.0598)	(0.0981)
No. Treated	1816	962	1186	650	611	403	416	346

Notes: Estimation based on Gateway to Research (GtR) and the Business Structure Database (BSD) for the period 2004–2016. ATT effect estimated using a 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	0.0387*	0.212***	0.0475***	0.166***
	(0.0190)	(0.0396)	(0.0108)	(0.0251)
Turnover	0.0651	0.301***	0.0442	0.146**
	(0.0375)	(0.0723)	(0.0227)	(0.0479)
No. Treated	1239	876	2816	1488

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 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 $t + 5$.

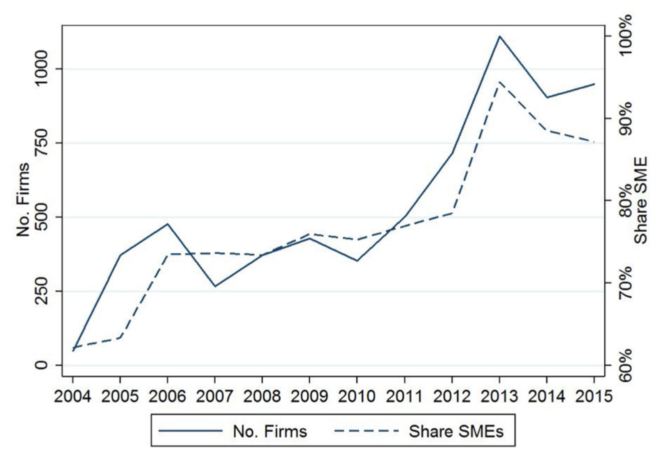


Fig. 6. Trend in the number of firms and the share of SMEs supported by Innovate UK.
Notes: Statistics based on Gateway to Research (GtR) and the Business Structure Database (BSD) for the period 2004–2016 for UK firms participating to Innovate UK funded projects. Share of SMEs calculated as the number of SMEs (less than 250 employees) over the total number of firms funded by Innovate UK. Minimum number of firms in 2004 equal to 74.

UKRCs support has a positive and statistically significant effect on employment and turnover growth only in the case of projects above the first two deciles of the relative grants size distribution. Thus, small grants relative to the firm size do not affect firms' performance, while relatively larger grants seem to have an increasingly positive effect on the employment and turnover growth. This evidence is in line with our previous results, as small and medium firms receiving relatively larger grants are more likely to experience employment and turnover growth as a consequence of the UKRC support, in respect to large firms for which relatively smaller grants might be less effective. In fact, treated firms in the top five deciles of the relative grant size distribution are usually small firms with an average initial employment below 50 employees, which manage to create around 20 new jobs 5 years after receiving large UKRCs-funded grants relative to their size, but very small grants in absolute terms. Similarly, the same firms starting with turnover below £2.5 m scale-up very quickly thanks to relatively large R &D grants funded by RCs in respect to their initial size, increasing their turnover by almost £750,000 over a 5-year period. At the other end of the scale, grants which are large in absolute scale but small relative to the size of large firms with more than 250 employees have no significant effect on the employment and turnover growth.

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

	SMEs Only				SMEs v Large			
	Pre 2012		Post 2012		Pre 2012		Post 2012	
	ST	MT	ST	MT	ST	MT	ST	MT
Employment	0.0751***	0.115**	0.0416**	0.0817***	−0.0376	−0.0581	0.163***	0.165**
	(0.0158)	(0.0355)	(0.0132)	(0.0243)	(0.0743)	(0.0916)	(0.0416)	(0.0802)
Turnover	0.247***	0.373***	0.156***	0.0566	−0.004	−0.0628	0.142*	0.0348
	(0.0280)	(0.0523)	(0.0354)	(0.0659)	(0.0889)	(0.174)	(0.0624)	(0.113)
No. Treated	1425	1381	2270	718	1079	1057	1618	256

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 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 $t+5$.

4.3. UK research councils heterogeneity

4.3.1. Projects funded by innovate UK compared with the Engineering and Physical Science Research Council (EPSRC)

Our data also allow us to analyse the effectiveness of research projects funded by different UK Research Councils in accelerating the growth 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: 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 from each other 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 University-Industry (U-I) partnerships.

Table 13 distinguishes between firms involved in projects funded by the EPSRC, Innovate UK, the Medical Research Council (MRC), and by the remaining RCs. Most of the treated companies received support from Innovate UK, more than 4000, while EPSRC-supported U-I collaborations involved about 900 of the firms in our sample. Firms involved in projects funded by EPSRC seem to benefit strongly in terms of both employment and turnover growth, increasing their scale by 24% in respect to comparable non-treated firms six years after the start of the project, while experiencing turnover growth by 26% after 6 years. Firms supported by Innovate UK experience smaller short-term and medium-term performance gains, both in terms of employment and turnover. Significant employment growth effects are limited to the medium-term only in the case of research projects supported by the MRC.[38] Finally, we also find a positive effect on medium -term employment growth only for projects supported by the remaining RCs.

These heterogeneous effects across UKRCs could also be driven by the participating firms' size. Focusing on the two main RCs supporting private firms, EPSRC and Innovate UK, in Table 14 we find that in both cases, the effects on employment and turnover growth are much larger overall for micro and small firms, with particularly strong impacts of 44–46% from EPSRC-funded projects 6 years after the beginning of the research project.

In Table 15 we further explore the heterogeneity of the EPSRC and Innovate UK by disentangling the effects of Innovate UK-funded U-I projects that, as all EPSRC-funded projects, involved a university partner versus Innovate UK projects that did not involve a university. Approximately 67% of our sample's Innovate UK-funded firms partnered with a university. Contrary to expectations we find larger ATTs for both employment and turnover growth in the short and medium-term for firms participating in Innovate UK projects which do not involve a university partner. One possibility is that these non-university Innovate UK projects are closer to market than those involving universities, and this is leading to stronger commercial impacts on participating firms in the short and medium terms. It is difficult from our data, however, to identify the precise nature of the R&D being conducted as part of any specific project so this interpretation remains somewhat speculative.

4.3.2. Evolution of innovate UK funding after the regional development agencies

Finally, we focus our attention on projects supported by Innovate UK in order to analyse the dynamic evolution of its funding strategy especially after the abolition of the Regional Development Agencies (RDAs) in 2012. As discussed in Section 3 and documented in Fig. 6, a range of innovation support schemes were transferred to Innovate UK after 2012, shifting its focus towards the support of SMEs. The SME share in the total number of supported firms rose to an average of almost 90% between 2013 and 2015. Therefore, in Table 16 we test whether the shift in the funding strategy of Innovate UK in 2012 had any effect on the performance of supported SMEs. Specifically, we compare the impact on the performance of SMEs supported by Innovate UK before and after 2012, relative to comparable unsupported firms in these two periods. Both before and after 2012, supported SMEs experienced faster employment and turnover growth in both the short and medium term. While there is no statistically significant difference between the two periods for the short-run employment effects and the size of the medium-term employment effect, the impact on turnover growth was much more significant statistically before the policy shift. However, comparing the group of supported SMEs with their large firm counterparts in the last four columns in Table 16, we see that SMEs achieved significantly stronger performance improvements than supported large firms after the shift in Innovate UK policy in 2012, while there were no differences between the two groups before. This evidence clearly indicates that the shift in Innovate UK focus after 2012 had a significant impact on the performance of supported firms, increasingly

[38] One tentative reason could be that the objective of much of the MRC-funded research will likely be to discover and test new drugs. Hence due to its nature, the research process may take longer, while the required long testing process, as well as potential patent applications, before the outcomes of the research are placed into the public domain and hence commercialised, may also imply that performance effects, in particular on turnover growth, may take longer to materialise. While currently out of reach in our sample period, one might conjecture that long-run effects may be stronger.

targeting at a larger number of SMEs, and fostering the innovativeness and economic growth for a broader sample of smaller firms.

5. 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. 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 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 which prove robust across a range of different estimation methods and techniques. First, firms involved in UKRC-funded projects grew around 6% faster in the short-term and 22% in the medium-term than similar firms which did not participate to UKRC projects. Second, this effect is stronger 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 reinforce those of other studies which have suggested – albeit on the basis of a more partial and largely case-based assessment – the benefits of public support for private R&D and innovation. Our analysis also suggests new insights related to how the characteristics of grant recipients, and the nature of research collaboration, effect the impact of public support. For the UK, where recent policy announcements point to significant increases in public support for private R&D and innovation in future years, our central results are reassuring: increasing levels of public support for R&D and innovation will have significant effects on future growth.

Our sub-sample results, however, raise some questions about whether the current focus of R&D and innovation policy in the UK is consistent with maximising additionality. Policy in the UK currently focuses 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 high-productivity businesses. Indeed, during our study period, our analysis of the Gateway to Research database suggests that 65 per cent of public support for business R&D and innovation in the UK was allocated to firms in the top quartile of the productivity distribution. Our results suggest that support provided to these already highly productive firms has limited additionality and growth effects. Additionality would be greater where support can be allocated to smaller firms with lower pre-award productivity. The size of grants – relative to the size of the firm – also seems important in shaping additionality and could be used along with prior productivity to guide the allocation of support. Over recent years UK innovation policy has also adopted a strong sectoral focus. Our results provide support for this focussed approach suggesting that additionality is greatest in more R&D intensive industries.

Our study is subject to a number of limitations. First, at this point we only consider the direct impacts of public grant 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 et al., 2017). Both should be considered in future studies. Secondly, as mentioned in Section 3.3.2, propensity score matching does not fully eliminate concerns that unobservable factors may explain grant allocation and post-grant performances. For instance, many of the firms participating in UKRC funded projects (although not all small firms) will also be receiving R&D tax credits.[39] As no data is available on which firms receive R&D tax credits we are unable to explicitly condition our matching on whether or not a firm receives an R&D tax credit, or the value of any tax relief. As any additional R&D investment carried out by a firm as a result of participating in a UKRC-funded project may increase the R&D tax relief received, it is conceivable that our results may also capture the effect of this second public innovation support instrument. Third, data linking, and the timing of some grant awards in recent years mean that 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 unobservable endogeneity bias. Further research is needed to investigate new approaches to improve the identification strategy, and in this regard information on all grants applications, including the unsuccessful ones, would greatly improve the robustness of the policy evaluation. Finally, our study focuses 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.

Conflict of interest

We have no conflict of interest in relation to this article.

Acknowledgements

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Appendix A

See Tables A1–A3.

[39] See UK Government (2018), "Guidance on Research and Development (R&D) tax reliefs" for information on Government definitions and qualification criteria for SMEs and large firms (available at https://www.gov.uk/guidance/corporation-tax-research-and-development-rd-relief).

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-Sáez and 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 and Ziedonis (2012) *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 et al. (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) Return over assets (ROA)	No significant effect No significant effects Positive No significant effect
Karhunen and 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 et al. (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 et al. (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 Business Administration (SMBA) for data on government R&D subsidy	2000–2007	Value-added productivity (value added/number of employees, in logs)	Positive
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 effect Phase 2 grant: No sign. Positive effect No sign.
Wang et al. (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 et al. (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 and 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 society' (IST) sub-programme (EU firms)	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
Bellucci et al. (2016) *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 subsidised and non-subsidised 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 (log) employment or turnover growth between time t-1 and t + 2 (BSD).
Medium-term Growth	Average (log) 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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