Department for Business, Energy & Industrial Strategy

THE IMPACT OF PUBLIC SUPPORT FOR INNOVATION ON FIRM OUTCOMES

BEIS Research Paper Number 3

March 2017

Contents

Acknowledgments

We are grateful to members of a steering group from BEIS, Innovate UK, the National Measurement System and HMRC: Ed Woolley, Mike King, Dan Hodges, Peter Lumb, Tim Harper, Thomas Bousfield and Atalay Dabak. We also extend our considerable gratitude to Dr. Monica Costa Dias of the Institute for Fiscal Studies who provided expert methodological advice throughout the study and comments on earlier drafts. Errors and omissions remain the responsibility of the authors alone.

Executive summary

Context

Frontier Economics was commissioned by the Department for Business, Energy and Industrial Strategy (BEIS) and Innovate UK to study the economic impact of public sector support for private sector innovation.

The analysis focuses on policies providing direct support for business innovation through grants, loans, advice and access to specialist services operated by Innovate UK (a non-departmental body sponsored by BEIS) and the National Measurement System (NMS).

We examine how receipt of support affects firm-level economic performance measured in terms of **survival**, **employment** and **turnover** up to 5 years after support. We do not consider explicitly the impact on productivity given the short time series of post-treatment data available. However, recent evidence that turnover growth is a precursor to productivity growth suggests that looking at other indicators of firm performance is a critical step in assessing the impact of such policies.

Our study focuses on the *outcome additionality* of support. To our knowledge this study represents one of the first attempts to do so using firm-level micro data on programme participation and economic performance for the UK.

Approach

Data sources

We draw on administrative data from Innovate UK and NMS to identify which firms received support through a number of programmes. Innovate UK schemes are largely (not exclusively) made up of grants for R&D. Support from NMS is defined as purchasing contract research or other services. We define separate measures of treatment for each body and treatment year (defined as the year in which treatment began for support which spans multiple years). Our support data cover the period from 2008 to 2012.

These data are matched at the enterprise level to the annual Business Structure Database (BSD), which includes information on almost all firms in the UK. The BSD contains a number of business characteristics (legal status, ownership, location, industry and age) and performance metrics (turnover and headcount employment). These metrics define our key outcomes of interest (with ‘survival’ proxied by the firm being observed in the BSD). Other variables are used in our modelling. We also include information on whether an enterprise is observed in the Business Enterprise Research and Development (BERD) dataset to proxy for its innovative behaviour. We observe outcomes up to 2013.

Methodology

We adopt a **propensity score matching** (PSM) approach combined with **difference-in-differences** estimation. We first model the likelihood that a firm with a given set of characteristics will receive a particular treatment. Treated firms are then matched, on the basis of this propensity score, to similar non-treated firms which form the control group. We carry out the matching within categories of firm defined by age, employment group and broad industry types. Along with the matching exercise, this helps to ensure that treated firms are matched with similar-looking control firms, in particular since the impact of treatment on survival is likely to be quite heterogeneous across age groups.

Differences in outcomes between treated and control groups are observed up to five years post-treatment. For turnover and employment outcomes, we also net off the average baseline (pre-treatment) difference between the treatment and control groups to yield a difference-in-differences estimate of the impact of treatment.[1] We carry out a number of checks which suggest that, as far as we can establish, the necessary assumptions for our analysis are valid (selection on observables, common support and common trends).

Our preference to ensure a close match between treated and control groups means that we lose a large share of treated firms in the matching process; our results are therefore valid for the subset of firms that remain in our analytical sample. However this means our results are more robust: we find evidence that common trends holds and can be more confident that we have controlled for the key drivers of selection into treatment. Any evaluation of business support programmes is likely to face similar trade-off between robustness and broad applicability of the findings, and our work highlights the issue as a general one for policy makers to consider in designing, implementing and evaluating such programmes.

Relative to the entire set of treated firms, the firms that are captured in our analysis are typically smaller. This reflects difficulties in finding valid close matches for larger firms, particularly in sectors which are heavily prone to treatment (research intensive manufacturing and service sectors) where almost all large firms are likely to have received treatment or where it is hard to find a comparable, non-treated firm.

While we have matched as closely as possible on observable characteristics of the firms, there may still be factors which we have not observed or adequately proxied in our modelling which could partly account for some of the results. This could include expectations of future survival (not captured by past firm-level growth rates) leading firms to seek support for innovation.

[1] For survival, there is by definition no baseline difference as all firms 'survive' before they are treated.

Main results

Our key results by source of treatment, outcome and age group of treated firm are summarised in **Figure 1** below.

Figure 1. Headline analytical results

Innovate UK

	Years following treatment				
	t+1	t+2	t+3	t+4	t+5
Survival effect: percentage points					
2 to 5	10.3%	15.3%	17.8%	19.6%	23.7%
6 to 19	5.1%	8.7%	11.9%	15.4%	16.3%
20 +	2.6%	5.0%	6.8%	8.5%	11.0%
Average	***5.3%***	***8.7%***	***11.1%***	***13.9%***	***16.2%***
Employment effect (difference-in-differences): headcount					
2 to 5	1.8	2.6	2.9	5.1	2.9
6 to 19	6.0	8.3	22.1	13.5	-1.6
20 +	64.4	80.2	75.0	67.8	45.8
Average	***24.8***	***32.3***	***39.0***	***31.6***	***16.8***
Turnover effect (difference-in-differences):£000s					
2 to 5	-7	65	34	180	-3
6 to 19	6	-178	776	2,148	2,414
20 +	14,380	16,634	25,560	10,171	10,044
Average	***4,847***	***5,727***	***10,094***	***4,691***	***4,748***

NMS

	Years following treatment				
	t+1	t+2	t+3	t+4	t+5
Survival effect: percentage points					
2 to 5	14.7%	21.9%	21.1%	27.8%	32.6%
6 to 19	5.2%	8.1%	12.7%	15.2%	18.7%
20 +	2.4%	4.8%	7.0%	8.6%	13.9%
Average	***5.0%***	***8.2%***	***11.3%***	***14.2%***	***18.8%***
Employment effect (difference-in-differences): headcount					
2 to 5	0.2	0.3	1.0	1.9	-0.7
6 to 19	16.5	22.1	31.8	29.2	52.5
20 +	-5.2	25.3	13.4	13.8	40.9
Average	***5.4***	***21.1***	***20.4***	***19.0***	***40.5***
Turnover effect (difference-in-differences):£000s					
2 to 5	29	20	10	-92	-151
6 to 19	454	1,067	-4	3	2,470
20 +	1,457	4,480	742	6,748	337
Average	***847***	***2,430***	***322***	***2,942***	***1,246***

Significant at 5% level   Significant at 10% level

Source: Frontier Economics analysis of business support data and BSD.

Impacts on survival

- We find consistent evidence of positive, significant survival impacts which appear to be similar across both treatments.
- The presence of significant survival effects makes the interpretation of any employment or turnover effect difficult, as it generates a selection bias (of unknown direction) on the treated sample. Turnover and employment impacts should therefore be treated cautiously. This is a wider issue for studies looking at the impact of business support programmes on firm-level performance.
- Survival effects grow over time, rising from 5 percentage points one year after treatment, to 11 points after three years and 16 percentage points (Innovate UK) or 19 points (NMS) after five years.
- Among control firms, survival rates for Innovate UK (NMS) are typically 94% (94%) after one year, 84% (85%) after three years and 75% (75%) after five years. Together, these results suggest that almost all firms receiving treatment survive for at least five years.
- Survival effects are larger for younger firms than older firms.

Impacts on employment and turnover

- Generally, we find positive impacts both on employment and turnover, though as described the survival effects make these difficult to interpret.
- Employment effects are often statistically significant (in particular for Innovate UK), though turnover effects are less often so.[2]
- Looking at the period two to four years post-treatment,[3] we find additional headcount employment of around 30-40 extra employees on average (Innovate UK) or around 20 on average (NMS); the differences reflect different average sizes of firms treated by each organisation. This equates to an increase of around 10-15% against a counterfactual outcome for each treatment.[4]
- There is more variation in turnover effects. Over the same horizon, they are in the order of £5 to £10 million additional turnover per year (Innovate UK, equating to around 10-25% additional turnover compared with a counterfactual) or £0 to £3 million (NMS, equating to around 0-10% additional turnover).
- Expressed in terms of additional headcount employment or turnover, the effects are unsurprisingly much smaller for younger firms (which tend to be smaller) than older firms. As a proportion of the estimated counterfactual outcome, there is no clear age effect.

Aggregated across the sample we observe for each treatment, the magnitude of additional employment and turnover effects appears very large relative to the size of grants given or payments received (though measuring this precisely is difficult). This suggests a degree of caution in interpreting the employment and turnover results, which could relate to the survival bias highlighted above. **However the size of any bias would have to be extremely large in order for there to be no additional employment or turnover impact.**

Our results focus on the impacts on the treated firms alone, and do not take into account any possible spillover benefits to non-treated firms. This suggests the overall impact of support may be larger than identified here.

---

[2] This significance reflects the impact on the *level* of additional turnover or employment. We also express results in proportional terms against a counterfactual outcome; however estimates of the statistical significance of these effects would require bootstrapping standard errors which was not feasible given the time available and the computationally demanding exercise being carried out. Note that the standard errors of the difference-in-differences estimator do not account for the fact that propensity scores are modelled and so may understate the true errors.

[3] We are generally more confident in interpreting effects at this duration. It is unlikely that we would expect employment or turnover to be increased much more quickly given lags between treatment and impact. When looking at five years post-treatment, we have only a single year of treatment data (2008) to rely on.

[4] The counterfactual is the baseline outcome for treated firms, plus the observed average growth rate amongst the matched controls.

Options for further analysis

Our work gives some initial evidence that when private firms receive public sector support for innovation, their economic outcomes in terms of survival, employment and turnover are improved. Further work could consider:

- Alternative definitions of ‘treatment’, such as variation by size of grant;
- Replicating the analysis in future years when more outcome data are available, allowing for a fuller assessment of the trajectory of impacts on turnover and employment to be made and initial analysis of the impact on measures of productivity. Given evidence from the literature that productivity impacts may take four or more years to realise, the replication exercise may be able to start picking up robust estimates of trends in productivity impacts when at least another two years or so of data are available, allowing researchers to look at impacts spanning multiple treatment years up to six years after treatment begins.
- Considering alternative ways to define control firms, such as restricting attention only to those firms who have sought some form of public support to grow or innovate in the past, or who are known to be R&D active.
- Further exploration of the survival impact, including using information on the nature of why firms do not survive to explore whether those receiving support are less likely to be taken over or less likely to go under (or both).
- Further analysis of the survival bias, including additional non-parametric analysis within the current approach (making assumptions about which firms would otherwise not have survived to bound the bias), or alternatively more demanding estimation methods to model selection into treatment, survival and outcomes separately.

Introduction

Frontier Economics was commissioned by the Department for Business, Energy and Industrial Strategy (BEIS) and Innovate UK to study the economic impact of public sector support for private sector innovation.

The analysis focuses on various policies providing direct support for business innovation through grants, loans, advice and access to specialist services operated by Innovate UK (a non-departmental body sponsored by BEIS) and the National Measurement System (NMS).

Innovate UK

Innovate UK is the UK's national innovation agency. The organisation works with people, companies and partner organisations to find and drive the science and technology innovations that will grow the economy - delivering productivity, new jobs and exports – and aiming to keep the UK globally competitive in the race for future prosperity.

It works across the whole economy and with different parts of government (including Whitehall Departments and Research Councils) to deliver cross-Government programmes which bring a range of different support instruments to bear on both the demand and supply side to promote innovation investment by business in new technologies and growth of industries of the future.

Its support mechanisms range from rapid and flexible support for early stage micro companies with limited resources in sectors such as the creative industries through to larger multi annual programmes for multi-national research intensive companies investing in large scale R&D projects in areas such as the vehicle manufacturing sector dominated by large companies with significant supply chains.

National Measurement System

The UK, like all developed nations, has a national measurement infrastructure that ensures a robust system of measurement and forms an essential component of being part of a global economy. At its core, the NMS ensures that measurement in the UK is consistent with the global common system of measurement units: the International System of Units – the SI (*Système international d'unités*).

The common SI system of units underpins much of the daily use of measurement in the UK. However, there are many areas of measurement such as in chemistry, biology and food science which are not currently directly linked to the SI system of units. Primary measurement underpinning these areas is established and disseminated through reference methods and/or materials. These areas are often where new measurement knowledge needs to be developed to tackle emerging needs.

Internationally, each country has one National Measurement Institute (NMI), whose role is to take the lead in international representation and to underpin delivery of a measurement infrastructure consistent with the SI system. In most countries, there are one or more Designated Institutes (DI), who support the NMI by delivering specific measurement capabilities and are recognised internationally as the lead measurement organisation for a particular physical or other quantity.

In the UK, the National Physical Laboratory (NPL) is the UK's NMI and works in partnership with five designated institutes:

- LGC (formerly the Laboratory of the Government Chemist)
- NEL-TUV (formerly the National Engineering Laboratory)
- NGML (National Gear Metrology Laboratory)
- NMRO (National Measurement and Regulation Office)
- NIBSC (National Institute for Biological Standards and Control)

This network of leading measurement capabilities forms the core of the UK's measurement infrastructure which is directly supported by Government through the NMS, with the exception of NIBSC, which is funded via the Medicines and Healthcare products Regulatory Agency (MHRA).

The project builds on work carried out by BEIS (2014) which used a propensity score matching approach applied to data from two innovation-related surveys to estimate the impact of public sector support on firms' innovation outputs, including R&D intensity, use of technical information, product and process innovation, sales of novel products and workforce technical skills.

This study extends the work to explore the impact on firm-level economic outcomes, in particular firm survival, employment and turnover. Drawing on an initial literature review, we identified a lack of robust quantitative evidence relating public sector support for innovation to additional firm-level economic outcomes. A data scoping exercise highlighted combinations of datasets (in particular matching management data on the firms in receipt of innovation support with outcome data from the Business Structure Database) and a methodology (difference-in-differences estimation combined with propensity score matching) that could address this gap credibly.

There is a large evidence base on the link between public support and greater R&D and innovation activity, and an extensive literature linking innovative behaviours to firm outcomes. There is also evidence linking public innovation support to economic outcomes, though to our knowledge this study represents one of the first attempts to do so using firm-level micro data on programme participation and economic performance for the UK.

Our key findings are that:

- Support for innovation provided by Innovate UK and NMS has a **positive, significant impact on firm's survival**.
    - Observed between two and four years after treatment begins, supported firms on average are around 8 to 12 percentage points more likely to survive than similar non-supported firms.
    - These effects are larger for younger firms.
- There is a **positive, often significant effect on employment outcomes**.
    - Observed two to four years after treatment begins, we find evidence of around 30 to 40 additional employed on average (Innovate UK) and 20 or so additional employed (NMS).
    - Patterns by firm age are less clear-cut for employment than for survival.
- There is **mixed evidence on the impact on turnover** when looking at relatively short-term post-treatment effects.
    - Typically effects are positive (on average, turnover increases by around 10% to 25% (Innovate UK) and 1% to 10% (NMS), but are rarely significant at the 5% level. The exception is for Innovate UK where significant effects are found towards the end of the post-treatment period analysed (four to five years after treatment).
    - There are no consistent patterns by age of firm.
- The significant impact on survival generates a **selection issue** for impacts on turnover or employment, and the direction of the selection bias is ambiguous. This makes the interpretation of turnover and employment effects more difficult.

The rest of the report is organised as follows. The next section sets out the context and rationale for the analysis, highlighting the ways in which the public sector supports business innovation in the UK and previous evidence on the issues examined. We then describe our modelling approach and data sources, alongside some preliminary descriptive evidence on the nature of the treatments and treated firms identified. We then report our key findings, before concluding and offering some next steps for further analysis. More detailed empirical results are set out in series of Annexes.

Context of the study

Public support for innovation in the UK

Innovation is a key driver of economic growth. The rate of technical progress features as a fundamental determinant of the long-run rate of growth of output per capita in established theoretical models of economic growth. Innovation can result from a number of activities, including investment in Research and Development (R&D), and other ‘intangible investments’ in knowledge.[5]

A recent review of available evidence found that private rates of return to investments in R&D are estimated to be around 20-30%, with social returns being typically two to three times larger (Frontier Economics, 2014). The greater social returns reflect benefits that cannot be appropriated by the investor (knowledge ‘spillovers’), and provide a clear economic rationale for public support of innovation investments. Other market failures which support the need for public intervention include asymmetric information between businesses and those providing private sector funding for innovation, and co-ordination failures where successful innovation requires collaboration across multiple economic agents or access to facilities that would not be in the sole economic interest of a single firm to provide. A summary of market and other failures rationalising public support for innovation is in Technopolis (2014).

Public policy can address these market failures by supporting private sector innovation in a number of ways, including:[6]

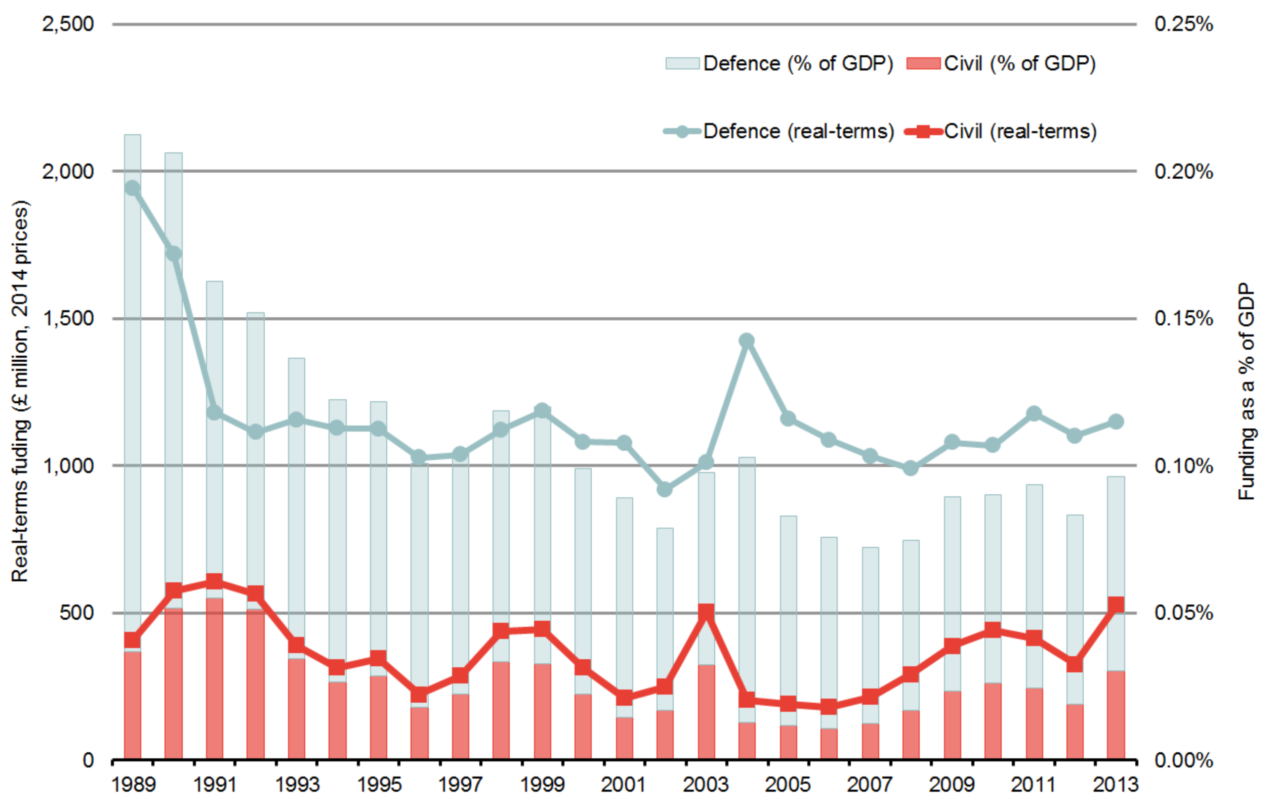
- Direct support to private innovation and research:
    - Providing direct grants and loans for R&D funding;
    - Providing advice and support related to innovation; and
    - Providing access to facilities and platforms (including means to aid collaboration) which facilitate innovation but which private companies may not in themselves have incentives to invest in.
- Providing guarantees to incentivise private sector finance for innovation;
- Fiscal incentives (e.g. tax credits);
- Demand-side support, for example, stimulating public organisations to be more innovative and to procure increasingly from innovative firms.

[5] Following the classification proposed in Corrado et al. (2005), intangible investments consist of: computerised information (including computer software and databases developed for a specific firm’s use); innovative property (including scientific R&D, costs of licensing and copyright, product design and development, exploration of minerals); economic competencies (including firm-specific human capital, market research and brand development, investments in organisational capital and structure).
[6] Taxonomy adapted from OECD (2014).

- Public research policy, such as developing the national science base, including funding research carried out by the public sector in universities and other research institutes.

Our study focuses on the first group of policies, those providing direct public support to private sector innovation. As of 2013, business and private non-profit organisations in the UK performed R&D activities worth approximately £18.4 billion, with £1.6 billion (8.9%) of this funded directly by the UK government. Around £1.1 billion of this was spent on defence and £0.5 billion on civil R&D. Government funding made up around 3.1% of the value of business sector civil R&D and 66% of the value of defence R&D. In real terms, both civil and defence R&D spending by government has increased since the first half of the 2000s, to levels seen in the early 1990s. Relative to GDP, total investment is around 0.1%, again higher than the mid-2000s but around half the level seen in the early 1990s (see **Figure 2**).

Figure 2. Government funding of R&D performed by the business sector, 1989-2013



Source: Frontier Economics analysis, based on data from Office for National Statistics, UK Business Enterprise R&D datasets 2013. Cash figures converted to real terms (2014 prices) using GDP deflators from HM Treasury. Note: does not include indirect support such as R&D tax credits.

Annex 1 gives more detail of a number of recent UK policies aimed at supporting civil business research and innovation. The focus of this study is direct support for civil R&D.

Past literature

Programmes of public support for innovation could generate economic impact through the following 'logic model':

1. **Input additionality**: public support leads to greater private-sector R&D activity, or at least is not fully crowded out by reductions in private-sector activity, leading to an overall increase in economy-wide R&D levels.
2. **Output additionality**: Higher R&D activity leads to increased innovation e.g. patents, new products and processes.
3. **Outcome additionality**: Innovation results in improved outcomes for firms e.g. increased turnover, employment, exports and productivity.

The majority of existing literature examines specific parts of this logic chain. For example, there is a large evidence base on the link between public support and greater R&D and innovation activity, and an extensive literature linking innovative behaviours to firm outcomes.

There is also evidence linking public innovation support to economic outcomes, often looking at specific programmes, or looking at aggregated impacts of total support on industry-level measures of productivity. Studies in other countries have used firm-level data on treatment and outcomes to look at outcome additionality, though to our knowledge we are among the first to do so for the UK. In addition, few papers have combined administrative data on programme participation with administrative data on firm performance as we do.[7]

Evidence on input additionality

The evidence broadly suggests that public support to innovation leads to greater R&D expenditure overall, suggesting that it does not simply fully crowd out private sector R&D which would otherwise have taken place.

Becker (2015) and Frontier Economics (2014) survey the empirical evidence and find, based on firm-level studies in a number of European countries, evidence of additionality effects of direct R&D subsidies. The What Works Centre for Local Growth (2015) look specifically at evidence from programme evaluations for whether grants, loans and subsidies for innovation lead to greater R&D spending overall. Of the 18 studies they identify as robust,[8] eight find positive impacts, eight find mixed impacts and only two find no impact or actively harmful effects. They note that only seven of these studies allow for a direct assessment of crowding out effects (because both private and public R&D are observed), and that these studies support the idea of a small crowding in effect. Some

[7] Some firm-level studies have used one-off surveys of programme participants and non-participants, introducing potential non-response biases into the estimates, and also meaning that longer-term impacts cannot be traced out.

[8] The paper considers only studies that rate at least a 3 on the Scientific Maryland Scale, where changes in outcomes for a treated group are compared with those for a control group ('difference in differences'). The studies vary in the degree to which the control group represents a credible counterfactual for outcomes for the treated group.

studies have looked at the variation in the effect by type or generosity of support. Guellec and de la Potterie (2003) find that a $1 increase in direct public funding for private sector R&D translates into an increase in private R&D of around $0.70 in the long run (that is, total R&D increases by $1.70), and that additionality is strongest with subsidisation rates of 4-11%. Gorg and Strobl (2007) use Irish data between 1999 and 2002, finding that the crowding in or out effects depends on the size of the firm and the size of any R&D incentives. They find no significant impact on private R&D for large, foreign multinationals, but a significant crowding in effect for smaller firms receiving relatively small R&D incentives. Crowding out became more likely as grant size increased.

Evidence on output additionality

Some studies have also assessed the impact of public support for innovation to the production of R&D outcomes such as patents, new products and process innovation. In their review, the What Works Centre for Local Growth (2015) identified 16 studies looking at innovation outcomes, of which eleven found largely positive effects, two found mixed results and three found no impact. There did not appear to be a discernible relationship with the particular outcome identified (e.g. patenting, or new products or processes being introduced).

In addition, BEIS (2014) examine the impact of innovation grant support on innovation performance in the UK. They find that this form of public support leads to greater innovation performance, particularly among SMEs and large firms. Measures of innovation performance include R&D investment, collaboration, employing STEM graduates, and introducing novel products to the market. The study also finds evidence of crowding in (approximately 30 percent) in the short term. Cerulli and Poti (2012) examine separately whether an Italian R&D policy influenced R&D expenditure, and whether this then led to innovation as measured by patent creation. It finds positive effects in both cases, with R&D expenditure leading to a 3.5% increase in the number of patents. Ruegg and Feller (2003) find evidence at the US Advanced Technology Programme generated additional outputs such as publications and patents.

Evidence linking innovation activity to firm performance

Analysis of the impact of R&D investment on private returns has typically used a production function estimation approach. Frontier Economics (2014) find a wide range of returns on such investment through a review of the existing literature, with average private returns of 33% across studies looking at impacts at the firm-level (31% when restricted to UK studies only).

Studies have also evaluated the private returns to different forms of innovation – namely, product and process innovation. The evidence base has used two approaches to do this, both of which have found positive effects of innovation activity on firm outcomes. One approach separates R&D investments into ‘product’ and ‘process’ in order to separately evaluate the returns to investment of each type. Griliches and Lichtenberg (1984) and Hanel (2000) find that process R&D yields higher returns. The second approach examines the returns to specific product and process innovations, treating R&D spending as an input to these innovations. A cross-country study by Griffith et al. (2006) and a study by Hall et al. (2009) find that product innovation yields larger benefits than process innovation.

A recent contribution by Roper and Hewitt-Dundas (2014) examined factors associated with firms' innovation outcomes (new products, processes and the share of sales derived from innovative products). They find that 'knowledge stocks' measured by past patenting have a weak, negative effect on innovation, suggesting some rigidity or path-dependence in innovation behaviours. Innovation is positively affected by R&D investment and 'external search' measured by things like innovation partnerships with other firms. This suggests that public support which encourages firms to develop new collaborations could improve innovation outcomes, perhaps through improving the capacity of firms to identify and absorb the ideas generated by others.

The links between public support and outcomes

Some studies have evaluated the impact of specific public R&D programmes on performance at an aggregated level using a production function methodology. Salter and Martin (2001) summarise nine studies to conclude that US spending on agricultural research programmes improved productivity in that industry. Outside of agriculture, the literature has shown mixed evidence of the returns to public-funded R&D. Haskel and Wallis (2010, 2013) find evidence that publicly funded R&D through government departments, research councils or higher education does have a significant impact on private sector productivity outcomes. Frontier Economics (2014) finds evidence that scientific research council spending is associated with improved private sector productivity.

UK-specific studies on the relationship between public support and outcomes have focused on the aggregate impact of these programmes, rather than the firm-level impact. PACEC (2011) calculated that the UK Collaborative R&D programme created 13,350 jobs and a Gross Value Added of £2.9bn. Regeneris Consulting (2010) estimate the total amounts of new sales, Gross Value Added and new jobs created by Innovate UK's Knowledge Transfer Partnerships (KTP), drawing on stated additionality from surveys and administrative data from the KTP programme. The precursor to KTP, the Teaching Company Scheme, was evaluated by SQW (2002) to determine the aggregate turnover and employment impacts.

Studies in other countries (summarised in Annex 2) have more closely followed the approach taken in this report, combining firm-level data on programme participation with economic outcomes to evaluate the impact on firm performance. Of the studies identified by the What Works Centre for Local Growth (2015), the impact on key outcomes is summarised in **Table 1**. While these studies have found mixed effects, it is notable that none of them have found a negative impact on programme participation, and in most cases (other than productivity) a majority of studies find broadly positive effects.

Table 1. Summary of impact on economic outcomes from firm-level studies

Outcome	Number of studies	Positive effect	Mixed effect	No effect	Negative effect
Productivity	9	4	1	4	0
Sales, Turnover, Profit	12	7	2	3	0
Employment	9	6	2	1	0
Other	11	6	3	2	0

Source: Frontier Economics analysis, drawing on What Works Centre for Local Growth (2015).

More recently, SQW et al. (2015) evaluated the impact of Smart, which since 2011 has been run by Innovate UK. Smart offers SMEs funding to carry out R&D projects. Part of the evaluation drew on survey data obtained both from firms who had successfully received funding (‘treated’) and those whose application was considered high enough quality to receive funding but where budget constraints prevented the firm receiving support from the scheme (‘control’). Using difference-in-difference methods and the resulting survey data, the study assessed the impact of Smart on observed turnover, employment, propensity to export and R&D investment roughly 2-3 years after support and also on forecast performance roughly 5-6 years after support.

Whilst the report concluded that, considering all the evidence assessed as part of a mixed methods approach, there was evidence that Smart had a positive impact on the beneficiaries, the analysis found no statistical significant impact on the outcome variables using an econometric approach. There were significant positive impacts found for sub-groups (those receiving ‘proof of concept’ awards, start-up firms, those outside the South East) for some measures.

Analytical approach

Introduction to the approach

We are looking to answer the question, “what impact does support for innovation have on outcomes for firms that receive support?” In particular, we are interested in understanding the impact on firm performance, measured by turnover and employment, but also recognising that an additional impact may be that firms survive longer than they otherwise would have. We describe these outcomes of interest in more detail below.

To answer this question, we need to establish a credible counterfactual for what would have happened to those firms in the absence of intervention. By comparing outcomes for supported firms to this counterfactual we obtain a reliable estimate of the ‘additional’ impact of the intervention. The counterfactual is fundamentally unobservable and so needs to be estimated.

The most conceptually appealing approach is to compare outcomes for firms who receive support (the treatment group) with firms who did not (the control group), treating the latter as a counterfactual. However, firms do not receive support at random: they select into applying for support, and those who receive support are further selected from those applying (where support is assigned competitively).

Given these hurdles, it is highly unlikely that simply looking at outcomes for non-supported firms alone would provide a suitable counterfactual: they will differ systematically from supported firms in a number of ways. We therefore adopt a *propensity score matching* (PSM) approach (see Rosenbaum and Rubin, 1983).

We first model the likelihood that a firm with a given set of characteristics will receive a particular treatment. This ‘propensity score’ can be estimated for firms regardless of whether they received the treatment or not.

Treated firms are then matched, on the basis of propensity score, to similar non-treated firms which defines the control group. The average outcome (survival, turnover or employment one to five years after treatment begins) is computed for the treatment and control groups, the difference between them giving the *Average Treatment Effect on Treated firms* (ATT).

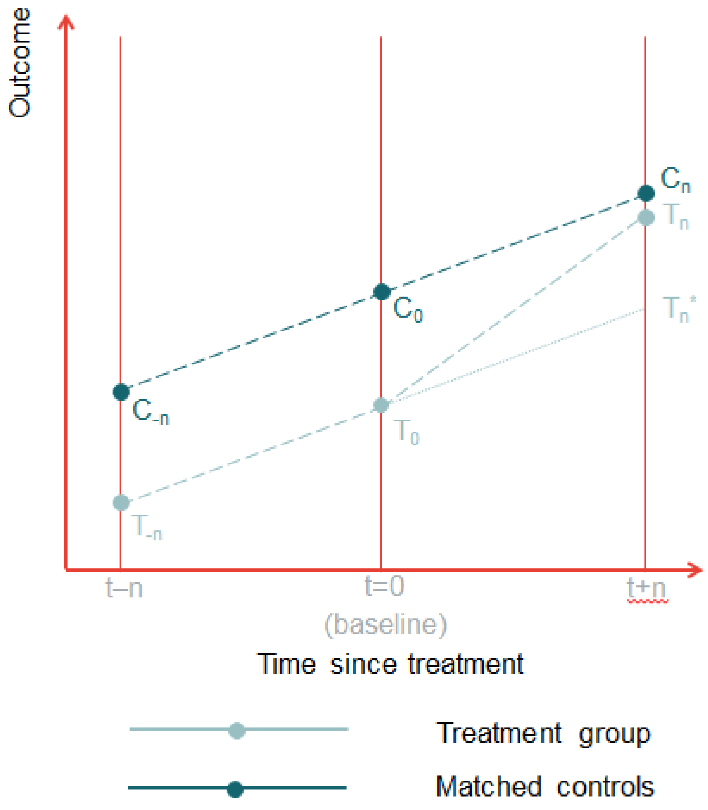
Finally, for turnover and employment, we net off the average baseline (pre-treatment) difference between the treatment and control groups to yield a *difference-in-differences* estimate of the impact of treatment.[9] Although the matching process should ensure that the treatment and control firms have similar baseline turnover and employment measures, it is possible that differences remain because the matching is based on the overall propensity score which is also affected by other covariates (such as industry, location,

[9] For survival, there is by definition no baseline difference as all firms ‘survive’ before they are treated.

treatment history and so on). We therefore want to net these off to get an estimate of the impact.

Consider the illustration in **Figure 3** below. At baseline (period t), the average outcome among the control group is larger than that in the treatment group ($C_0 > T_0$). Estimating the ATT could yield negative treatment effects if this remains the case after treatment (in the example below, in period t+n, we still observe $C_n > T_n$ and the ATT would simply be the difference between the two). However, it is clear that the gap between treatment and control firms has narrowed after treatment, and it is this narrowing that we would want to ascribe as the impact of treatment. Instead of comparing T_n with C_n, we instead should compare T_n with our best estimate of the counterfactual outcome for treated firms (call this T_n^*), which is to assume that the baseline gap between the two groups would otherwise have persisted.

Figure 3. Estimating the treatment effect: 'difference-in-differences'



Source: Frontier Economics.

The difference-in-differences estimator can be expressed both in terms of levels (additional employment or turnover generated by treatment) or as a proportion of the counterfactual outcome for treated firms:

- Levels: $(T_n - T_n^*) = T_n - (T_0 + (C_n - C_0)) = (T_n - T_0) - (C_n - C_0)$
- Proportions: $[(T_n - T_0) - (C_n - C_0)] \div [T_0 + (C_n - C_0)]$

Assumptions required

We are interested in finding the effect of support on firm outcomes. Let Y1 be an outcome of interest (e.g. employment three years after receiving support) for firms that receive support, let Y0 be the outcome for a firm that does not, and let S be an indicator of whether or not the firm received support for innovation. We want to estimate the ATT:

$$E(Y_1|S = 1) - E(Y_0|S = 1)$$

The second term is not observed, but is observed for firms who are not supported:

$$E(Y_0|S = 0)$$

If we are willing to assume that, given a propensity score P(X) estimated based on a set of control variables X, the expected outcomes do not depend on treatment status, then we can estimate the treatment effect since:

$$E(Y_0|S = 1, P(X)) = E(Y_0|S = 0, P(X))$$

As a result we can estimate the ATT using the observable relationship:

$$E(Y_1|S = 1, P(X)) - E(Y_0|S = 0, P(X))$$

This is the **conditional independence assumption** (CIA). The CIA is sometimes referred to as ‘selection on observables’: the set of characteristics X used to estimate the propensity score is sufficient to characterise determinants of whether or not a firm is supported and its later outcomes.

Testing the CIA is difficult. It is possible to assess whether there are observable differences between the treatment group and (matched) control group using formal balancing tests once the matching procedure has been implemented. However, testing if there are unobserved characteristics which affect outcomes given treatment status is more difficult to prove. We describe the results of formal balancing tests and approach to selection on observables below. More detailed evidence is given in Annexes 5 and 6.

The validity of the PSM approach also depends on the **common support assumption** which says that there is overlap between supported and non-supported firms in terms of propensity score:

$$0 < P(S = 1|X) < 1$$

More simply: for a treated firm with a given propensity score, we are able to find a control firm with a similar propensity score with which to match. In our results we offer evidence that this holds; however in general given that our dataset contains many millions of untreated firms, we are able to find suitable matches for treated firms in almost all cases.

To implement the difference-in-differences estimator credibly, we need to be confident that, in the absence of treatment, any baseline gap between treated and control firms in turnover or employment would have persisted. For this assumption to be more compelling, the **common trends** assumption needs to hold: trends in the outcome variable before treatment are required to be similar for the treatment and matched control group. We would therefore wish to observe, for example, that $(C_{-n} – T_{-n}) \approx (C_0 – T_0)$. This is illustrated in **Figure 3** by the parallel growth in outcomes for treated and control in the pre-baseline period.

We test for the common trends assumption by examining pre-treatment trends in the outcomes of interest among our treated and matched control firms. Visual inspection of these trends suggests no systematic evidence that the common trends assumption is violated (see Annex 4).

Data sources

Treatment data: receipt of public support for innovation

We draw on administrative data from a number of public bodies to identify which firms received support through a number of programmes over time. Data came from three sources:

1. **Innovate UK**. We received a version of Innovate UK's public dataset of episodes of support provided through Innovate UK-managed programmes.[10]
2. The **National Measurement System (NMS)**. We obtained data on firms that had accessed free resources through the website and firms that had paid for contract research or measurement services. These services are not provided free of charge, but the payment received is thought to be significantly lower than the value of the services provided, so representing public support.
3. The **Department for Business, Energy and Industrial Strategy**. This dataset included information on financial and non-financial episodes of support delivered through a number of public UK organisations or schemes, including Innovate UK, the Design Council, the UK Office for Trade and Investment, the Intellectual Property Office, the Enterprise Finance Guarantee and Enterprise Capital Funds.[11]

[10] A public version of the data is available from https://www.gov.uk/government/publications/innovate-uk-funded-projects. We received a version including firm-level identifiers which allowed it to be matched with data on firm-level outcomes as described below.
[11] The dataset also contained information on support delivered through the UK Office for Trade and Investment (UKTI); however, UKTI support tends to focus more on generic support for business activity and export promotion, rather than innovation. We did not include this in our final measure of support received for innovation, but rather used access to UKTI as an explanatory variable in our modelling.

Treatments of interest

Our analysis focuses on two definitions of treatment, each recorded as simple binary (receive/do not receive) indicators:

- Receiving support from any of a number of schemes operated by **Innovate UK**, which are largely (but not exclusively) made up of grants for R&D;[12]
- Purchasing contract research or other services from **NMS**.[13]

We did not include the policies identified in the BEIS dataset, which are not exclusively (or even predominantly) focused on promoting innovation, but instead provide more generic support for business activity, access to external finance and export promotion. However, given that receipt of one or more of these schemes tells us useful information about a firm's desire to grow and to interact with government, and so may be correlated both with receipt of our defined treatments and our outcomes of interest, we did include them as part of the propensity score modelling as described more fully below.

We identify separate indicators by year of treatment, defined as the year in which treatment begins. Particularly in the case of grant-based funding, treatment can span a number of years but we ascribe treatment fully to the initial year.

The data we use cover the period from 2008 to 2012. Clearly this represents an atypical period of recent economic performance, given the scale of the financial crisis and recession. It is not clear that this impacts our results: our detailed findings break down the results by treatment year and we find little systematic difference. Further, to a large extent macroeconomic conditions could be considered a common shock affecting both treatment and control groups.

The number of sources covered in the support dataset for Innovate UK increases with time. This is partly due to a number of policies only being included in the data after they were begun to be managed by Innovate UK: Knowledge Transfer Partnerships and SMART/GR&D, for example, are only really reflected in our data from 2010 and 2011 respectively. Similarly, information on beneficiaries from the Small Business Research Initiative, first established in 2001, is only available from 2008 onwards. This suggests that we have an imperfect measure of Innovate UK treatment, though we can be more confident in the completeness of the data from 2008 onwards. We therefore begin our

[12] Collaborative R&D, Knowledge Transfer Partnerships, SMART/Grants for R&D, Small Business Research Initiative, Innovation Vouchers, Launchpads, European Programmes, Feasibility Studies, and a number of historical schemes previously provided by Regional Development Agencies and the old Department for Trade and Industry (DTI). Firms who are supported by other bodies supported by Innovate UK, such as Catapult Centres, are not included in this analysis.

[13] It would be possible to consider broader or narrower definitions of 'treatment' from NMS: for example, restricting attention to those purchasing research services only, or those engaging with NMS in any way such as accessing freely-available information. We were not able to use the latter definition as the NMS dataset did contained only an indicator of whether a firm had accessed information but not the year in which information was accessed.

analysis in that year. We do record measures of treatment in earlier years, which we use as control variables in our matching analysis.[14]

Data on firm-level outcomes and characteristics

The support dataset includes information on which firms have been supported by UK public organisations. In order to estimate the effect of support, we also need information on firm outcomes (namely, turnover and employment) and characteristics that can be used to carry out the matching exercise.

Our key dataset is the annual Business Structure Database (BSD), first collected in 1997, which includes information on all businesses in the UK that are liable for VAT[15] and/or have at least one member of staff registered for PAYE. In 2004, it was estimated that businesses listed in the Inter-Departmental Business Register, a live register of data collected by HM Revenue and Customs of which the BSD is an annual snapshot, accounted for almost 99% of all economic activity in the UK.[16] To all intents and purposes, therefore, the BSD can be treated like a census of firms in the UK.

Among other characteristics, the BSD includes firm-level information on:

- Turnover;
- Employment (headcount figure);
- Legal status (whether the business is a company, a sole proprietor, a partnership, a public organisation, or a non-profit making body);
- Ownership (immediately and/or ultimately foreign-owned);
- Location (we focus on Government Office Region);
- Industry (five-digit Standard Industry Classification codes), and;
- Year of birth.

Each of these variables, among others, was used in the matching model.

We matched data from the BSD to firms receiving support from Innovate UK or NMS using unique firm identifiers (the IDBR enterprise reference number). The support datasets did not contain these enterprise reference numbers directly; instead, Companies House Reference Numbers (CRN) were linked with equivalent enterprise reference numbers by the ONS. Match rates between CRN and enterprise reference numbers in the Innovate UK dataset improved over time from around a 63% match rate in 2007 to 90% in 2013. Following advice from ONS, we were not persuaded that further ‘fuzzy matching’

[14] The fact we have an imperfect measure of which firms received public support would tend to bias down treatment effects, since some of our ‘control’ firms will in fact have received unobserved public support for innovation. Note this could include support from other departments such as former-DECC and the Ministry of Defence.

[15] A business must be VAT-registered if its annual turnover is above a minimum amount. This amount is updated annually. Over the period in consideration for this study, the registration threshold ranged from £60,000 in 2005-06 to £79,000 in 2013-14.

[16] Source: http://discover.ukdataservice.ac.uk/catalogue?sn=6697.

(attempting to identify the enterprise reference numbers on the basis of company name and address) would yield significant additional matches.[17]

In linking the BSD to the support data, we used a lagged year of BSD – that is, we took the 2011 BSD data and linked it with support data from 2010, and so on. This was based on advice received suggesting that the way that the BSD was constructed meant that data could arrive with considerable lag.[18] We therefore have observed outcomes for all years between 2008 (the first treatment year in the support dataset) and 2013 (one year after the last year of support data).

We also defined a further variable which was a dummy indicator in each year taking a value of 1 if the firm was observed in the Business Enterprise Research and Development (BERD) sampling frame. BERD data are based on an annual survey focused on firms' R&D activity. The sampling frame is made up of around 28,000 firms in the UK who are known or believed to be actively engaged in R&D drawn from a variety of sources. A sample is drawn from this population to participate in the survey; data for other firms are then imputed to give a dataset containing records for each firm expected to be R&D-active.[19] The dummy variable for being observed in BERD therefore reflects whether a given firm is innovation-active in the sense of spending on R&D. We linked this variable with the BSD and support data using the enterprise reference number.

Outcomes of interest

Our key interest is in the impact of support for innovation on later firm performance, measured as **employment** and **turnover**.[20]

As a critical initial step before looking at turnover and employment outcomes, we first look at whether there is any impact of support on firm survival. Survival is defined as whether we observe the enterprise in the BSD t years post-treatment.[21]

---

[17] Again, this suggests that some firms we identify as control firms (not supported by Innovate UK or NMS) are, in fact, treated which would tend to bias down treatment effects.

[18] Data on the IDBR which underlies the BSD snapshot are obtained from a variety of administrative and survey sources, and can sometimes be imputed. Our version of the BSD datasets did not contain any timestamp reflecting precisely the period to which the observation corresponded. We were guided by previous best practice which suggested that a one-year lag was the most appropriate assumption; however, it is possible that for some firms the BSD data are more timely whereas for others the lags involved are even longer. To the extent that this variation in lag structure is similar for treatment and control groups it may not be an issue, although for firms with very long lags in data availability, it is possible that outcomes we assume to be post-treatment actually reflect pre-treatment conditions.

[19] More information on BERD can be found at www.ons.gov.uk/economy/governmentpublicsectorandtaxes/researchanddevelopmentexpenditure/qmis/ukbusinessenterpriseresearchanddevelopmentqmi

[20] Employment measures in the BSD are headcount, rather than full-time equivalents. There is a clear policy interest in understanding whether support for innovation affects firm-level productivity as well (whether turnover per employee or some measure of TFP). Given the timescales involved, an accurate assessment of productivity impacts would require a longer period of post-treatment outcomes, but would be an interesting extension to the work in future. Recent evidence (Du et al., 2013) that turnover growth is a precursor to productivity growth suggests that looking at other indicators of firm performance is a critical step in assessing the impact of such policies

[21] In principle it is possible to use information in the BSD to understand *why* firms exit – whether because of takeover or bankruptcy, for example. However this is possible at the level of the local unit whereas our main

It is essential to understand whether treatment impacts on survival in order to be able to analyse precisely the impact on turnover and employment. These outcomes are, by definition, only observed for firms that remain in business, implying that estimating the impact of treatment on turnover or employment also needs to condition on survival. However, if treatment affects survival, the selection of surviving treated firms is different from the selection of surviving non-treated firms. Hence, even if treatment is essentially random conditional on observed characteristics (that is, the conditional independence assumption holds), random assignment will not hold conditional on survival.

The implication of this is that if treatment affects survival, we cannot easily interpret any observed effects of treatment on turnover and employment since the direction of any induced selection bias is unclear:

- There may be a *negative* selection effect if firms that are able to survive as a result of receiving support for innovation are more marginal firms with lower turnover or employment than others;
- There may be a *positive* selection effect if support overcomes market failures (such as access to finance or informational barriers) which mean that firms who would otherwise be very successful do not survive.

One possible solution is to restrict the study of growth to groups of firms for which treatment does not affect survival. This limits analysis to certain groups but means we can be confident that turnover and employment effects are not contaminated by a survivor bias. We carried out some exploratory analysis to understand the groups of firms for which survival effects were likely to be small.[22] Based on this, we identified older firms (those aged 20+) as those where there was unlikely to be a significant impact of treatment on survival: these enterprises are already established, and support is more likely to be about encouraging new innovation within an existing product portfolio rather than helping firms to establish themselves and stay in the market. Middle aged firms (aged between 6 and 19) also showed relatively small survival effects whereas younger firms (aged 5 and under) tended to show a large impact of support on survival outcomes. We therefore carried out our main analysis within age group.[23]

It seems unlikely that we would expect substantial impacts on employment and turnover to emerge very rapidly – support for innovation needs time to yield new innovation and for this to be brought to market in a way that would affect firm performance. We therefore focus most of our discussion on results around two to four years following treatment. This is roughly in line with existing evidence from the empirical literature (summarised in

---

analysis is on the enterprise and there is no straightforward way to map between local units and enterprises (e.g. if one local unit within an enterprise exits but the enterprise as a whole survives).

[22] We regressed survival outcomes on a dummy variable for receipt of support interacted with a set of firm-level covariates, and looked at the joint significance of support for firms of different types. As is clear from our main analytical results, although our simple regression model suggested that selection effects would be insignificant for older firms, in our full matching specification (see **Figure 19**) we still find positive and significant survival impacts for the older age group (though the effects are relatively small compared with the survival impact for younger firms).

[23] For the full Innovate UK sample, firms aged 5 and under account for 20% of those receiving support (measured by number of firms), those aged 6 to 19 account for 41% of those receiving support and those aged 20+ account for 39% of those receiving support.

Frontier Economics, 2014) that it takes around 1–3 years for firms to turn new innovation into new revenue streams, and that it would take more time for firms to translate innovation support into new innovation. This suggests that impacts in terms of productivity could take even longer to materialise, consistent with evidence from other evaluations (see Annex B) which have found productivity impacts typically after around 4 or more years.

Data cleaning

Combining the data from the BSD, BERD and support datasets yielded a large analytical dataset spanning five separate years from 2008 to 2012 inclusive. In total, this dataset contained around 9.2 million observations (where an observation is a combination of firm and year).

We performed a number of cleaning and trimming exercises to the data, in part to remove obvious anomalies and in part to exclude outlier firms (in particular at the top of the employment and turnover size distributions) which may be difficult to match or which could skew the size of treatment effects substantially.[24] In particular:

- **Anomalous observations**. We exclude firms who have:
  - zero workers or zero turnover in any year they are observed, since they suggest misreported information or irregular firms;[25] and
  - one year growth rates (in turnover or employment) of over 50,000%, since growth rates of this magnitude would suggest the firm's turnover or employment is incorrectly reported in one of the years.

- **Very large firms**. We exclude any firms with turnover and employment above the 99th percentile of all values observed across the entire BSD dataset between 2008 and 2013.[26] We allow the threshold to vary by broad age class of firms, reflecting the fact that older firms tend to be larger and that our analysis is later carried out by age group.
- **Industries**. We exclude firms in sectors that are never or rarely treated, to avoid the possibility that they may be matched as controls to firms in very different industries. These sectors are: households as employers; public administration; employment services; accommodation and food; manufacturing of furniture, wood, paper and textiles; and wholesale, retail and repair of motor vehicles. For NMS specifically, we further exclude firms in arts, entertainment and recreation; real estate; publishing and media; and finance and insurance, where NMS support is very rare.
- **'Re-entering' firms**. We observe a number of firms that are present in the BSD in one year, absent in a subsequent year and then are re-observed (with the same

---

[24] In particular, very large firms treated firms may be hard to match, in principle, with any other firm given they are likely to have unique characteristics; similarly, very large untreated firms could enter the control group if they are sufficiently similar to treated firms on other dimensions. One or two very large firms entering the treatment or control group could dominate the averages, leading to misleading estimates of ATTs for a given treatment and outcome.

[25] We exclude firms who record no workers, including owners. It is possible, of course, that firms have no employees and these remain in our analysis.

[26] Cutoffs are defined as 89 employees or £11.5 million turnover for firms aged 2–5 years and 11,170 employees or £2,530 million turnover for firms aged 6 and over.

enterprise reference identifier) after that. It is not clear why this patterns should be observed (and we use absence from the BSD as an outcome measure for firm survival), and so we drop all such firms.

Additionally, our final analysis excludes firms that are under two years old, since we use two-year histories of employment and turnover as control variables in our matching model. This reduces our analytical dataset further.

Our final dataset, which also excludes those firms for which we were unable to estimate a propensity score or to find a matched control firm within the common support (see below), contains 4.3 million observations for Innovate UK and 3.2 million observations for NMS.

Model specification

We estimate a propensity score for each firm and treatment using a logit model relating a dummy for treatment with a set of characteristics. The model is estimated separately for each year of treatment (2008 to 2012) and, within year, for three broad bands of enterprise by age (aged 2 to 5, aged 6 to 19 and aged 20 and over), based on the preliminary exploration of groups for which survival effects were likely to be relatively small. The variables included in the specification are summarised in **Table 2**.

Accounting for selection into treatment

Variables included in the propensity score model should include all factors that influence both a firm's likelihood to be treated and its outcomes after treatment. Besides observable characteristics such as industry, ownership, location, and age, it would be important to also control for whether a firm is innovative and for firms' willingness to grow: organisations that do not plan to innovate and grow are unlikely to receive public support and would also be less likely to expand. Our approach in this respect includes the following controls:

- Including turnover and employment in logarithms and in dummies both at t-1 and t-2 allows us to control for both firm size and firm growth rates prior to treatment. Firms that are growing rapidly may be more likely to seek support for innovation and be more likely to grow in the future. Matching fast-growing treated firms to fast-growing non-treated firms is therefore important in dealing with possible selection on unobservables.
- We include a variable indicating whether the firm was found in the BERD dataset in any of the two previous years, as a measure of past involvement in R&D activities. We also include a variable that specifies whether the firm received support from any public source for innovation within the previous two years (e.g. for those observed in 2008 we look at whether the firm is also observed in the support datasets in 2006 or 2007). This tries to capture the idea that firms who receive support in the past are also more likely to receive support in the future, and acts as a rough proxy for the stage of the innovation cycle (firms who have received support in the recent past may be further along a development pathway than those who have not).

Table 2. Specification of propensity score model

Variable	Final specification
Size	Log of turnover and employment at both t-1 and t-2.[27] Dummies for 'size categories' for turnover and employment in each of t-1 and t-2: ● Employment categories: 2 or fewer employees; 3 to 9; 10 to 49; 50 to 249; 250 or more employees. ● Turnover categories: £0 to £100,000; £100,000 to £2m; £2m to £10m; £10m to £50m; over £50m.
Support from any innovation programme	Dummy variable for the firm being supported in t-1 or t-2 from any source (including BEIS programmes) in the support dataset.
Appears in BERD	Dummy variable for being in BERD at t-1 or t-2.
Industry, Ownership status, Region, Foreign-owned, Age	Dummies at t. We include 24 to 28 separate industry dummies,[28] 4 ownership status dummies, 12 region dummies, and a dummy for ultimately foreign-owned and single year age dummies.

Source: Frontier Economics. Note: Period t is the year of treatment. Support from any innovation programme excludes UKTI: Information on support from UKTI is only available from 2011. This makes it only possible to control for past support from UKTI in the form of a dummy for support in t-1 and in the case of treatment in 2012. We remove the UKTI control from the model to ensure consistency across years.

There may still be factors which we have not observed or adequately proxied in our modelling which could still mean that selection on unobservables remains an issue that could account for some of the findings. This could include expectations of future survival (not captured by past firm-level growth rates) leading firms to seek support for innovation.

Approach to matching

We adopt a radius matching approach: for each treated firm, we identify all non-treated firms with a very similar propensity score (we adopt a calliper of 0.001 from the modelled propensity score for the treated firm),[29] and use firms within this radius as control firms. We do not allow the match to take place between any firms within the calliper, however. Instead, we only allow a treated firm to be matched with control firms within the same broad size and industry groups, defined below.

[27] Note we do not include baseline (period *t*) measures as we only wish to include variables in our model which we are confident are not, in themselves, affected by the treatment. Given some uncertainty over the timing of the BSD variable described above, there was a risk that some measures of turnover and employment at period *t* would, in fact, be *post-treatment* rather than pre-treatment.

[28] The number of industry dummies depends on the definition of treatment, since arts, entertainment and recreation; real estate; publishing and media; and finance and insurance are excluded from the analysis when treatment is defined as support from NMS.

[29] Treated firms without any control firm within 0.001 of the estimated propensity score are deemed to be outside the 'common support' (see below) and excluded from the analysis. It is possible to assign differential weights to each control firm within the radius using a kernel matching approach which weights control firms closer to the propensity score of each treated firm more heavily; however these add significantly to computational time required and it was not feasible to implement within this study. Given a relatively narrow calliper it is unlikely that a non-uniform kernel weighting would have any substantial effect on the results.

Table 3. Employment categories for matching

Age band	Employment categories
2 to 5	<=2; 3 to 9; 10 to 49; 50+
6 to 19	<=2; 3 to 9; 10 to 49; 50 to 249; 250+
20+	<=2; 3 to 9; 10 to 49; 50 to 249; 250+

Source: Frontier Economics.

Table 4. Industry categories for matching

Broad Industry
Agriculture, mining and quarrying
Manufacturing
Construction, wholesale, retail, transport and storage
R&D, architectural/engineering information services, telecoms, utilities and education
Other services

Source: Frontier Economics.

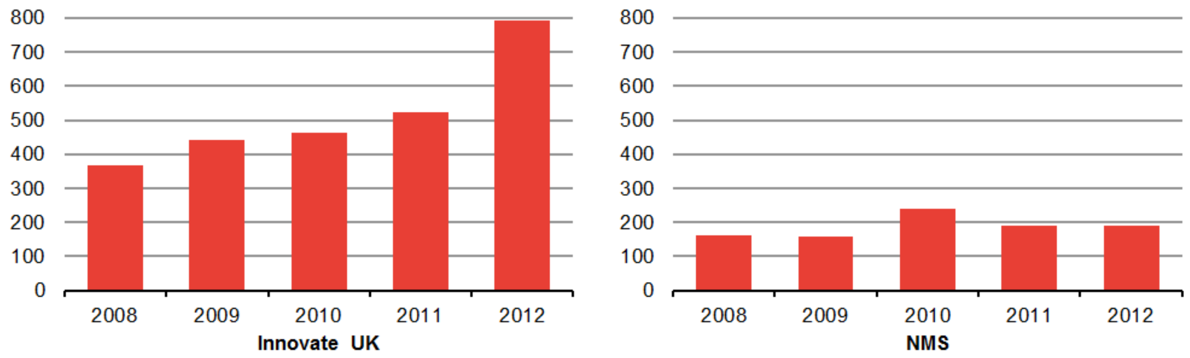
This ensures that there is a greater degree of comparability between treatment and control firms whilst still allowing the flexibility of matching based on the overall propensity score estimated on the basis of a number of other characteristics.

Descriptive evidence

This section presents the characteristics of treated and control firms in the final dataset, after data cleaning and matching were performed.[30] These are the mean attributes of the treatment and control samples, before we apply matching weights which are designed to align the characteristics as closely as possible.

Figure 4 below presents the number of firms treated by Innovate UK and NMS in our final analytical dataset.[31] Support from Innovate UK increases over time, in particular between 2011 and 2012, when the number of firms supported increases by nearly 50%. This is due to new programmes being introduced and existing programmes moving into Innovate UK's remit during this data period. For example, the Small Business Research Initiative was reformed and re-launched under Innovate UK in 2009, and Growth Vouchers were introduced in 2012. By contrast, the number of firms in the post-matching dataset supported by NMS remains broadly constant over time.

Figure 4. Number of matched treated firms by support year and treatment



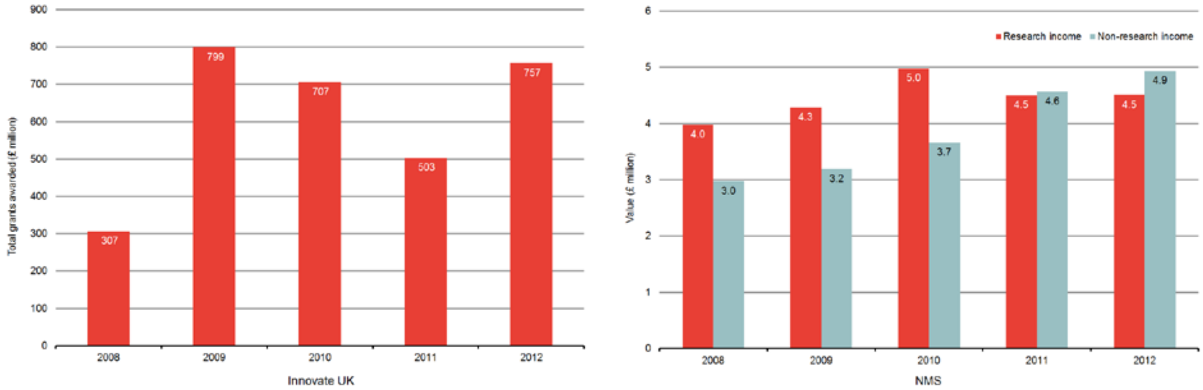
Source: Frontier Economics analysis of business support data and BSD.

All of the support programmes included in our analysis included some financial component. In the case of Innovate UK, we observe grant amounts awarded to the supported firm; in the case of NMS, we observe payments from the supported firm to the supporting organisation, for research or other services.

Figure 5 below shows the total amount of grants awarded through Innovate UK and of payments to NMS reflected in our support data. We see a significant increase in total grant awards from Innovate UK between 2008 and 2009, reflecting improvements in the coverage of schemes in the support data. For NMS there is a similar level of income observed in each year of the support dataset.

[30] Excluding treated firms for whom no propensity score could be estimated or no match could be found among controls within the calliper and within the groups within which matching was carried out.
[31] These are the number of 'matched treated' for which we are able to find a similar control firm.

Figure 5. Financial amounts involved in support of treated firms, by support year



Source: Frontier Economics analysis of business support data.

Distribution of treated firms

The figures below present breakdowns of the characteristics of matched treated and control firms for the Innovate UK and NMS treatments. Again, the distributions are raw mean characteristics of the treatment and control firms before matching weights from the propensity score estimation are applied. These distributions also refer to the matched sample, rather than representing the characteristics for all firms treated by Innovate UK and NMS.

Enterprise age

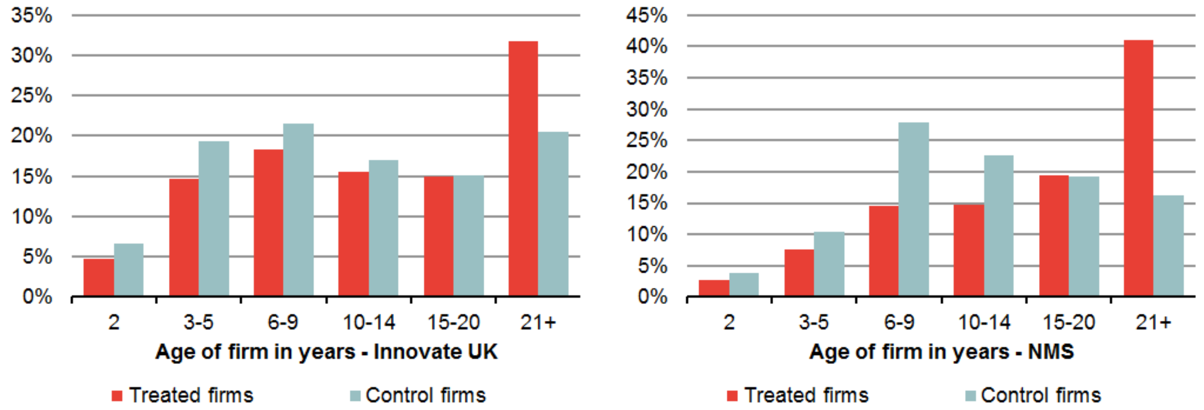
Figure 6 below presents the distribution of firms by age band. Supported firms tend to be older than control firms, especially for NMS.

In the Innovate UK treatment sample, older firms (aged 21 and over) are over-represented compared with control firms. For NMS, there are more pronounced differences: for example, firms aged 6 to 9 make up only 14% of supported firms but 28% of control firms. Firms aged 21 and over, on the other hand, make up 41% of supported firms but only 16% of controls.

Employment

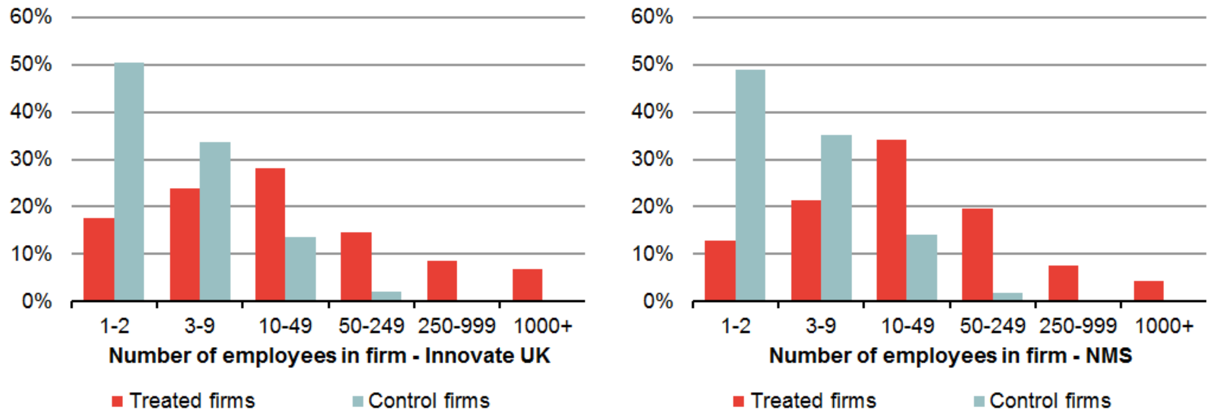
Figure 7 below presents the distribution of firms by employment band and treatment status. Generally, supported firms tend to be larger than non-supported ones. For instance, very small firms comprised of one or two people account for only 18% of Innovate UK-supported firms (13% for NMS), while comprising 50% of control firms (49% for NMS). Firms with 50-249 employees, by contrast, make up 15% of Innovate UK-supported firms (19% for NMS), but only 2% of control firms.

Figure 6. Distribution of matched firms by age group



Source: Frontier Economics analysis of business support data and BSD.

Figure 7. Distribution of matched firms by employment group



Source: Frontier Economics analysis of business support data and BSD. Note: employment defined as number of employees including owner.

Region

Figure 8 below presents the distribution of firms by Government Office Region and treatment. The shares of firms supported by Innovate UK in each region are almost exactly those of control firms by region, whereas NMS-supported firms have a slightly higher likelihood of being from the South East and a slightly lower likelihood of being from London, than control firms.

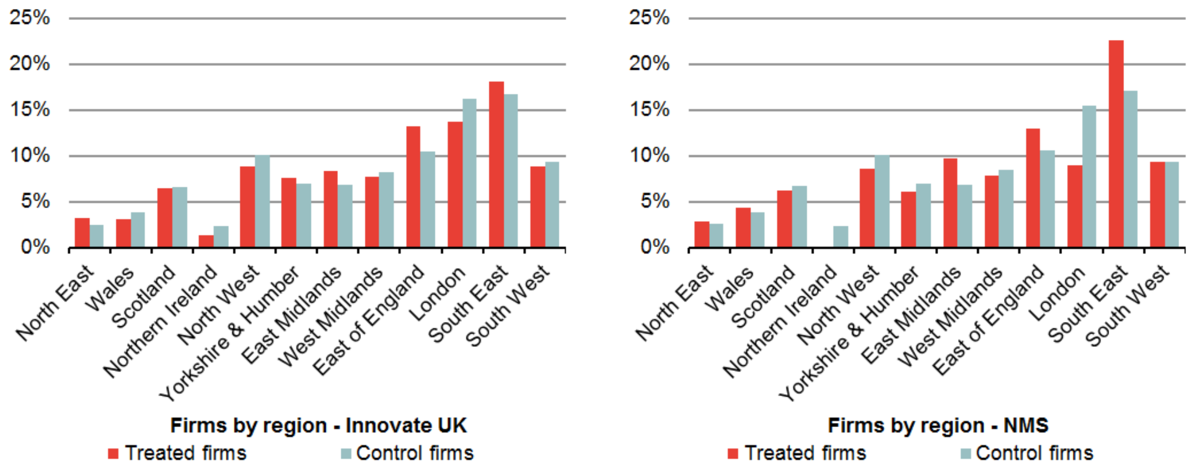
Industry

Figure **9** below presents the distribution of firms by industry. Supported firms tend to belong to a specific small group of knowledge-intensive industries – for Innovate UK, the top five industries combined account for 45% of all supported firms, and the single largest one (information services) accounts for over 13% of supported firms.[32] In the case of NMS,

[32] The rest of the top five is as follows: *Architectural & engineering services* (10.6%), *Scientific R&D services* (8.5%), *Other admin & support services* (6.1%), *Manufacturing - electrical products* (5.5%)

the top six industries account for 59% of all supported firms.[33] Note that these industries are not the same as those supported by Innovate UK – for example, information services is much less frequently supported by NMS, making up 3.6% of treated firms. Four industries (scientific R&D services; architectural and engineering services; manufacturing of electrical products; and other wholesale) are among the top six for both sources of support, however.

Figure 8. Distribution of matched firms by Government Office Region



Source: Frontier Economics analysis of business support data and BSD.

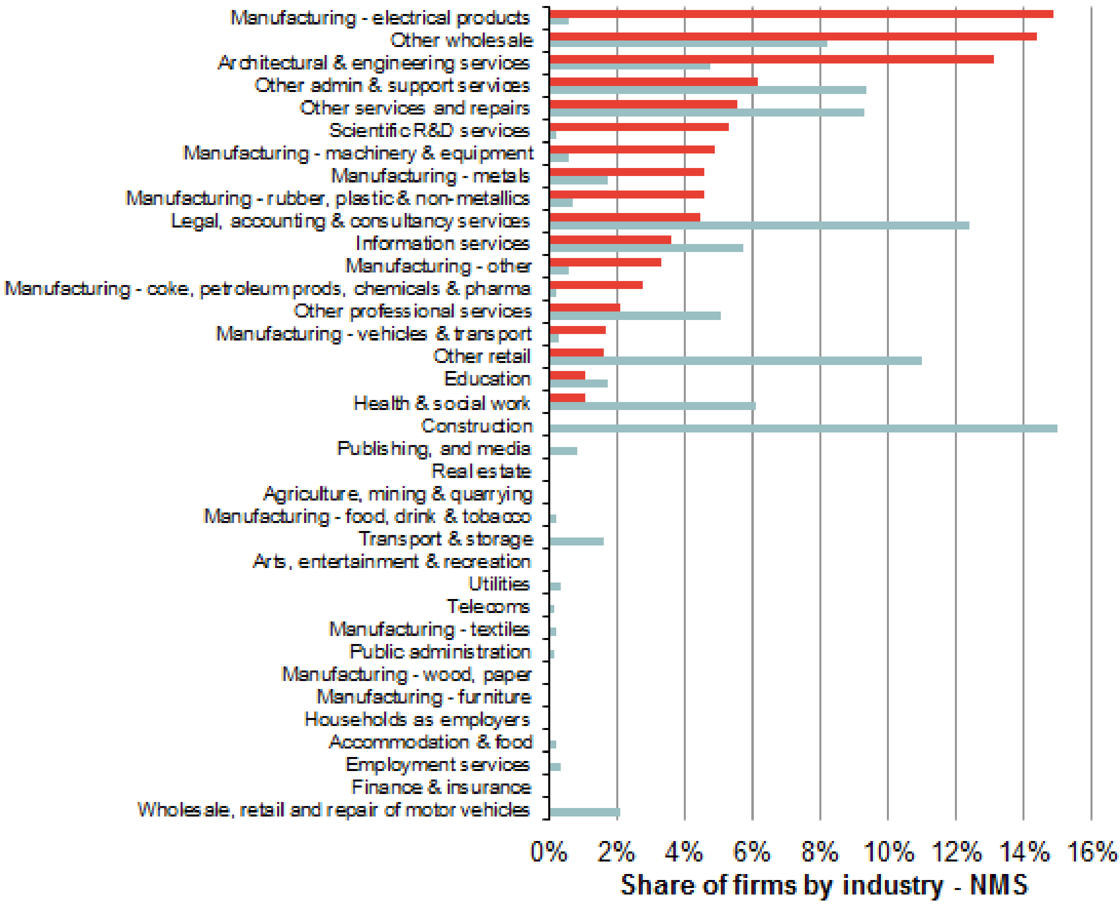
All of the industries mentioned above account for much larger shares of supported firms than they do of control firms. Other industries (such as legal, accounting and consultancy services; other retail; and construction), are naturally much more represented among control firms.

Turnover

Figure 10 below presents the distribution of matched firms by turnover bands. As with employment, supported firms tend to be larger in terms of turnover than non-supported firms. The biggest band for both groups is the £100k-£2m band, but the firms above it account for a much larger share of supported firms than of control firms. For very small firms, the situation is reversed – those with turnover of below £100k make up around one-third of control firms for each treatment, but only 16% of Innovate UK-supported firms and 9% of NMS-supported ones.

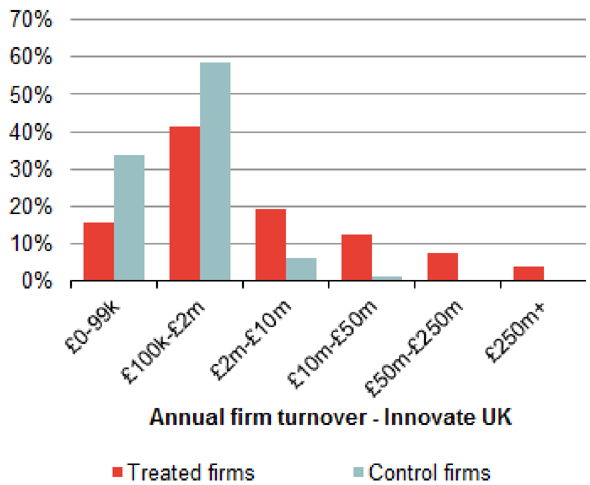
[33] *Manufacturing - electrical products* (14.9%), *Other Wholesale* (14.4%), *Architectural & engineering services* (13.1%), *Other admin & support services* (6.2%), Other services and repairs (5.5%), *Scientific R&D services* (5.3%).

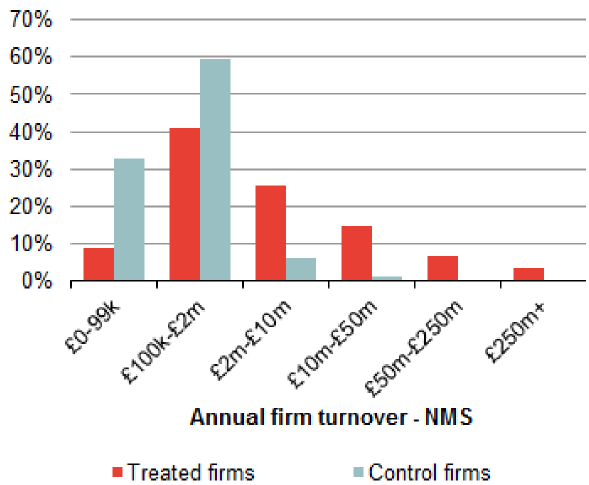
Figure 9. Distribution of matched firms by industry



Source: Frontier Economics analysis of business support data and BSD.

Figure 10. Distribution of matched firms by turnover bands





Source: Frontier Economics analysis of business support data and BSD.

Legal status and ownership

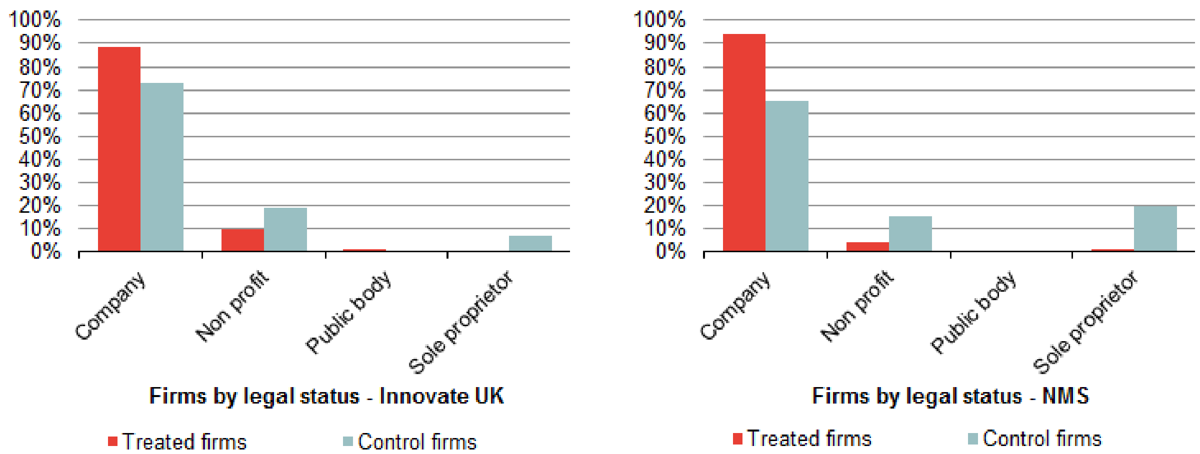
Figure 11 below presents the distribution of supported firms in the sample by legal status, and Figure 12 shows what share of supported firms are ultimately UK-owned and what share are ultimately foreign-owned.

Supported firms tend overwhelmingly to be companies, rather than public bodies or non-profit organisations, though Innovate UK supports non-profits relatively more often than NMS.[34] Supported firms have a higher likelihood of having foreign ownership than is the case with non-supported firms: approximately one-third of supported firms are ultimately foreign-owned, compared with 6-7% of non-supported firms. This may well reflect some of the patterns seen earlier by which supported firms tended to be larger, and that larger firms tend to be more likely to be foreign-owned.

Past support

Figure 13 below presents the share of supported firms in the dataset that have received support from Innovate UK, NMS, or any of the more general business support schemes included in the support dataset. Perhaps unsurprisingly, treated firms are considerably more likely than control firms to have received support in the past, and the proportion is higher for firms supported by NMS (35% of supported firms) than Innovate UK (17%).[35]

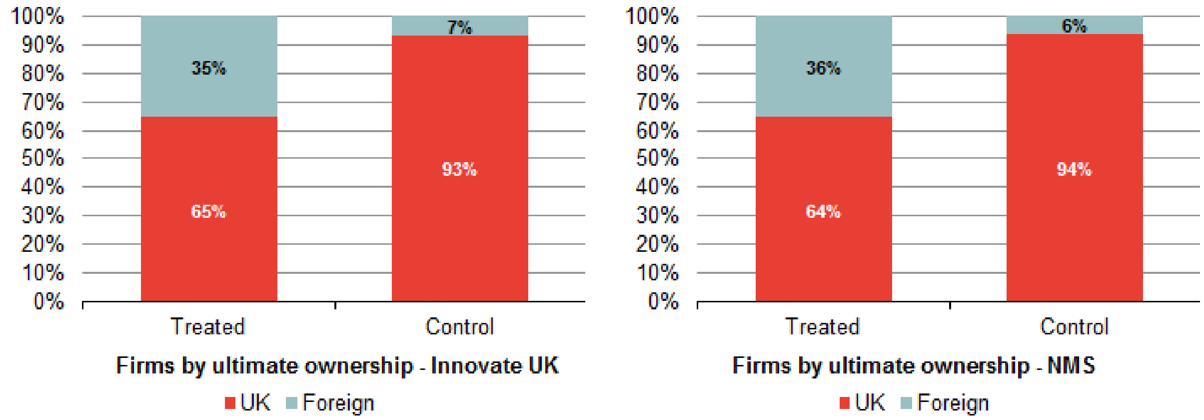
Figure 11. Distribution of matched firms by legal status



Source: Frontier Economics analysis of business support data and BSD.

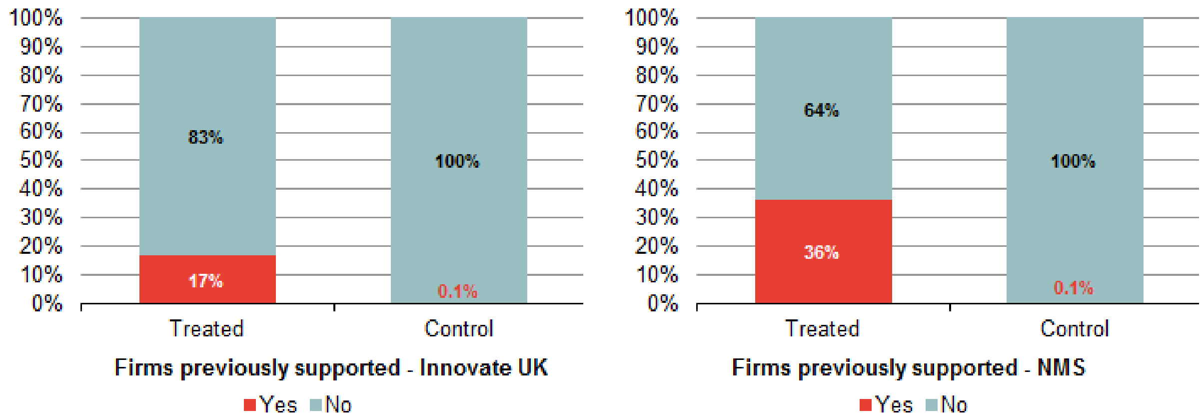
[34] This could reflect the nature of the definition of our support variable for NMS which focuses on using paid-for services. Alternative definitions such as seeking advice could look different.
[35] Note that our approach does not rely on only looking at firms receiving their first period of support. Any impact on survival, turnover or employment could therefore also reflect past histories of support received as well, in part. An interesting extension would be to consider only firms that, as far as we can tell, are receiving support for the first time.

Figure 12. Distribution of matched firms by ownership status



Source: Frontier Economics analysis of business support data and BSD.

Figure 13. Distribution of matched firms by previous support



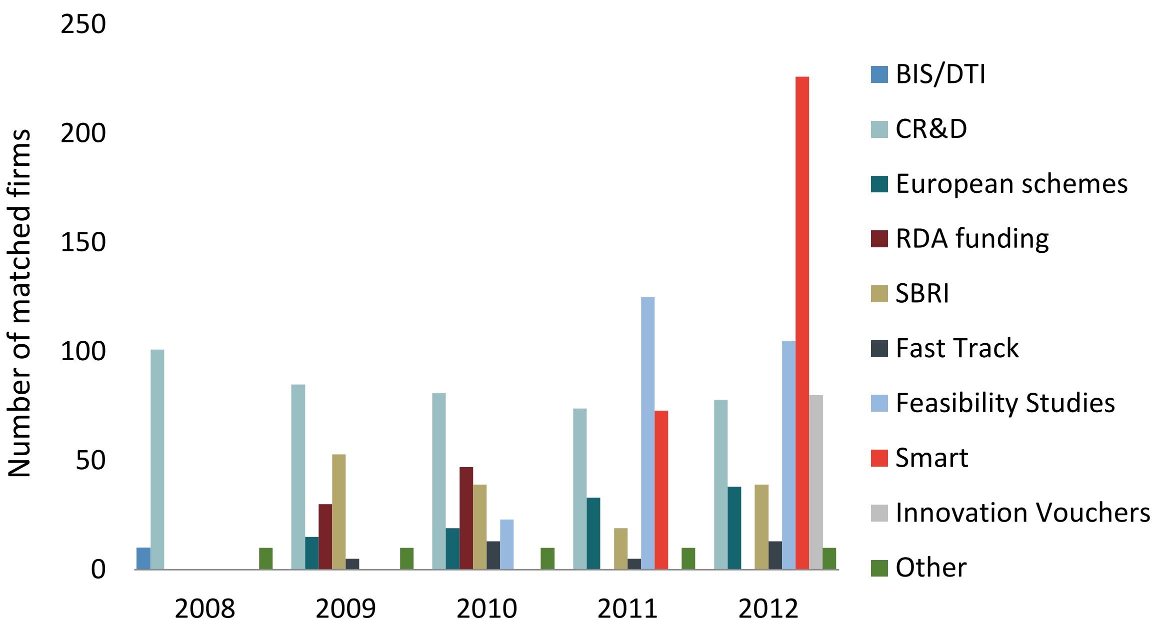
Source: Frontier Economics analysis of business support data and BSD. Note: past support defined as receipt of support from any source (including BEIS programmes not included in our treatment indicators) in 2 years prior to treatment.

Characteristics of treatment

For Innovate UK, it is possible to investigate the characteristics of treatment received over time: specifically, it is possible to know under which scheme support was provided, and in some cases the grant amount awarded.[36]

Figure 14 reports the number of matched treated firms in each year that received support under each of the schemes included in the Innovate UK dataset.[37] The distribution of firms across support schemes is consistent with the pre-matching distribution – it does not appear that firms supported under specific schemes are disproportionately likely to drop out in the data cleaning, propensity score estimation, or matching processes. **Figure 15** repeats the analysis for the value of funding, where this is known.

Figure 14. Number of matched firms supported by Innovate UK, by support scheme and treatment year

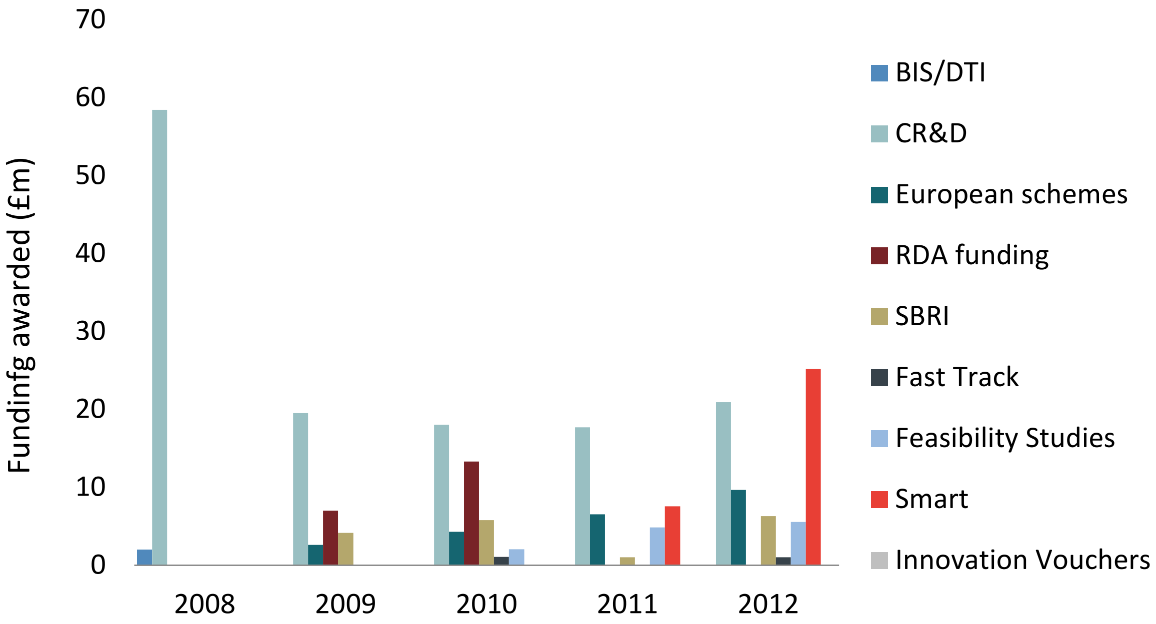


Source: Frontier Economics analysis of business support data and BSD.

[36] We observe grant amounts for around 30% of treated firms in 2008 and 70% in 2012. Note that we are only able to present information related to schemes that supported at least 10 firms in a given year given confidentiality rules stipulated by the Office for National Statistics.

[37] The 'Other' category includes all schemes with number of supported firms lower than 10, for which it was not possible to export the exact number of supported firms from the VML. The number of treated firms in this category has been arbitrarily set to 5 for illustrative purposes. Schemes included are: Knowledge Transfer Partnerships and Innovation Centres, as well as a small number of episodes of support provided under unknown schemes.

Figure 15. Funding awarded to matched firms treated by Innovate UK, by support scheme and treatment year



Source: Frontier Economics analysis of business support data and BSD.

Main results

Success of the matching exercise

Common support

For each treatment (Innovate UK and NMS) we ran, in total, 15 separate propensity score models (combining five treatment years and three age groups) using the specification described. These models were used to define a matched treatment and control group.

In propensity score modelling, there is always a trade-off between the appropriateness of the matches made and the extent to which it is possible to find matches for each treated firm. Given that the nature of support was likely to vary significantly by industry and firm age (and that our prior was that survival effects, which would contaminate our ability to interpret any employment and turnover impact, would also vary by age), we chose to match exactly within age and industry group. We also wanted to minimise the observed difference between treated and control groups in terms of size at treatment, as firm size could be a proxy for its capacity to innovate or absorb knowledge (e.g. employing specialist researchers); as a result, we also felt it was important to match within employment groups as well.

The large number of models, combined with a demanding calliper and approach to matching, meant that we sacrificed a relatively large number of treated firms. For Innovate UK, after the raw data had been cleaned and trimmed, we had 3,510 treated firms remaining. Of these, we found matched control firms for 2,665, losing 829 (24%). For NMS, we found matched control firms for 966 of the 2,201 firms observed after data cleaning, losing 1,235 (56%). Treated firms could be lost in two cases:

- Where they exhibited a combination of characteristics which perfectly predicted their being treated or not treated (and so were dropped from the propensity score estimation as no control or treated firm could be found with the same covariates). This accounted for relatively small numbers of lost firms in the treatment group.
- Where no match could be found within the calliper and the restricted set of firms from which controls were sought. This was the main reason for treated firms not being included in our final sample.

The evolution of the sample sizes from raw data (aggregated across treatment years) to final analytical dataset in shown in Table 5.

Our results represent average treatment effects for the successfully matched sample of treated firms. To the extent that the treated firms ‘lost’ in the matching process are observably similar to all treated firms, the effects may be seen as representative of all treated firms. If the firms lost have different characteristics to those that remain, some judgement will be needed as to whether the estimated effects would also apply to the wider sample of treated firms.

Table 5. Evolution of sample size, treated and control groups, by treatment

Treatment	Raw data	Cleaned and trimmed sample	With propensity score	Successfully matched (analytical data)
Innovate UK	8,560,201	8,431,361	5,781,194	4,598,462
	3,703	3,510	3,494	2,665
NMS	8,561,575	8,432,670	5,198,482	3,477,352
	2,329	2,201	2,100	966

Source: Frontier Economics analysis of business support data and BSD. Note: Top row within treatment shows number of control group firms, bottom row the number of treated.

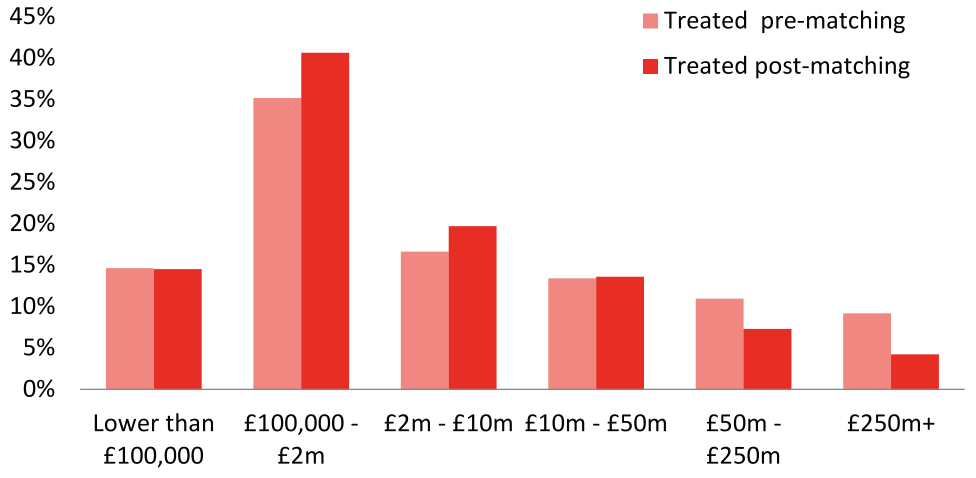
We compared the characteristics of all treated firms (after the basic cleaning and trimming of the raw data had been applied) with those in our final matched treated sample. Key results are presented below. Full results are in Annex 3.

For Innovate UK, compared with all treated firms, those in our final dataset tended to be slightly smaller (in terms of measured turnover or employment), less likely to have received support or conducted R&D previously (and so perhaps less ‘innovative’ in some sense), and less likely to be within the Scientific R&D or Education industries. As shown earlier, larger firms, those receiving past support or previously conducting R&D and firms in those research-based service sectors are more likely to be treated than the average firm. It therefore appears that we were often unable to find suitable matches among the control firms for firms with this combination of characteristics.

For NMS, treated firms in the final dataset also tended to be smaller and were less likely to have received support or conducted R&D. Moreover, matched firms treated by NMS were also less likely to manufacture electrical products as their main activity, and were typically younger (specifically, less likely to be aged over 20) than the initial set of treated firms.

Figure 16 shows the impact of the matching procedure on the distribution of turnover among firms treated by Innovate UK. Approximately 20% of treated firms in our dataset after cleaning, trimming, and computing propensity scores (‘pre-matching’) have a turnover of £50 million or more. However, it was not possible to find a suitable match for over 50% of firms with turnover over £250 million, and approximately 30% of firms with turnover between £50 million and £250 million. As a result, only 11% of matched treated firms have turnover of £50 million or more. It is of course not surprising that it is more difficult to find suitable matches for very large firms; one implication, though, is that the average treatment effects identified in our results may slightly overstate the impact on survival (since very large firms are probably more likely to survive), and understate the impact on the average level of employment and turnover (since the impact on these larger firms would pull up the average effect in levels, if not necessarily relative to the estimated counterfactual, measured in our results).

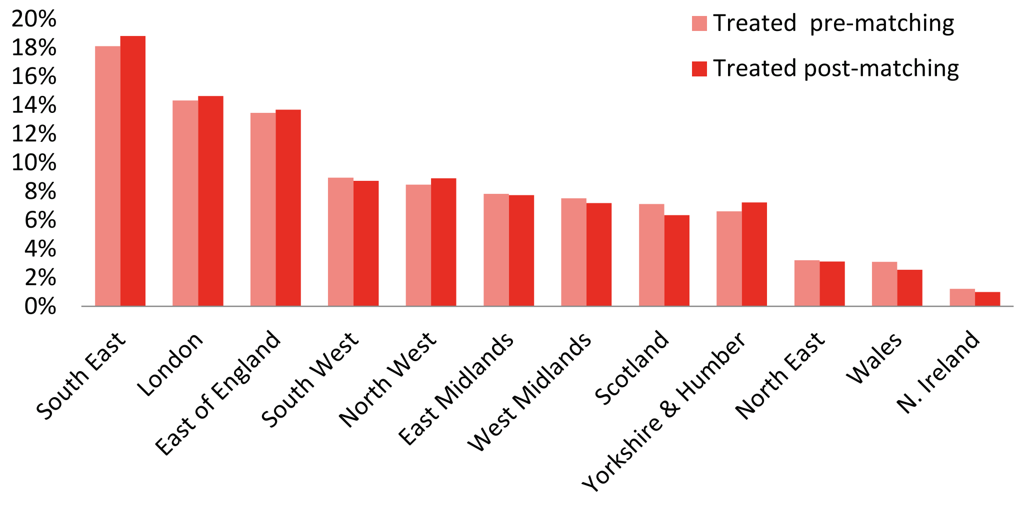
Figure 16. Distribution of turnover among firms treated by Innovate UK, by matching status



Source: Frontier Economics analysis of business support data and BSD.

As shown in **Figure 17** below, the matching procedure had little impact on the distribution of Innovate UK-treated firms across regions. The picture is similar for legal status and firm age distributions (see Annex 3). We find that organisations in our post-matching treated sample are somewhat more likely to ultimately UK-owned, which could reflect the findings on size (as larger firms are more likely to be ultimately foreign-owned).

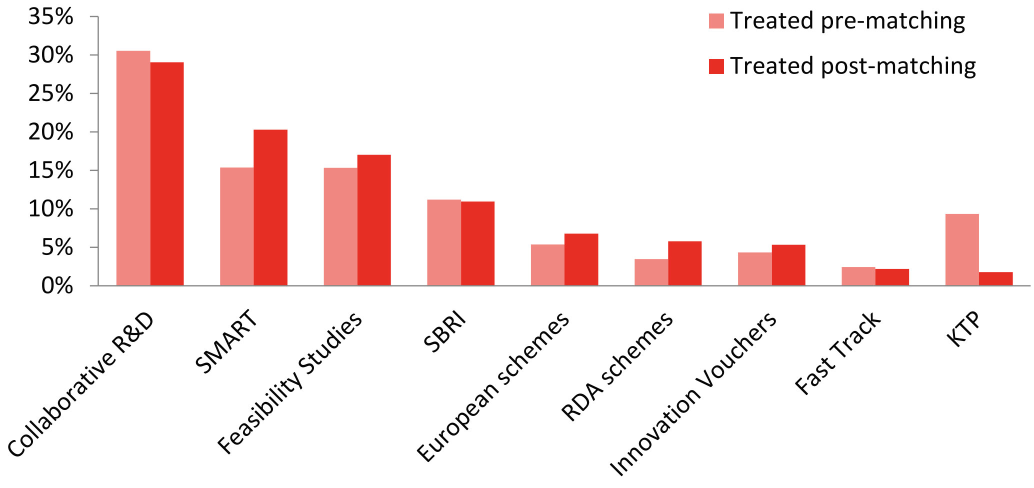
Figure 17. Location of firms treated by Innovate UK, by matching status



Source: Frontier Economics analysis of business support data and BSD.

For the case of support from Innovate UK, we can also observe the characteristics of treatment received by a subset of the firms lost in the matching process (**Figure 18**). Matched firms are less likely to have been involved in Knowledge Transfer Partnerships (KTPs) and more likely to have benefitted from the Smart grant scheme.

Figure 18. Distribution of Innovate UK support schemes among treated firms, by matching status



Source: Frontier Economics analysis of business support data and Business Structure Database.

These differences in the composition of treatment may be linked to the characteristics of firms lost in the matching process:

- Smart is targeted at small and medium enterprises, and SMEs are somewhat more likely to be in the final matched treated sample than large firms;
- KTPs involve collaboration between business and universities, colleges, and research and technology organisations. Education providers are a relatively large proportion of treated organisations lost in the matching process.

Comparability of matched treated and control groups

After the matching procedure, we run balancing tests to check how similar treated firms are to the control firms that were matched to them. Separate tests are run for each propensity score model, a total of 30 across the two treatments. Rather than present all of these tests separately, we summarised the number of instances across these tests when each covariate included in the propensity score model was found to be statistically different (at the 5% level) between treated and control groups before and after the matching procedure.[38] For Innovate UK, we find 595 instances out of 1,053 (57%) where the samples are significantly different before matching, but only 2 out of 1,053 instances after matching (0.2%). For NMS, we find 562 out of 959 instances (59%) before matching,

[38] Note that not all covariates are seen in 30 separate propensity score models, either because some industry covariates are used only in the Innovate UK specification, or because some covariates are dropped from a particular propensity score model as they predict success or failure (treatment or non-treatment) perfectly. We therefore show the number of instances where the covariate is included and then the number of times its mean is significantly different between treated and control groups before and after matching weights are applied to the control group sample.

and 2 out of 957[39] after and zero after. This suggests that, at least statistically speaking, the matching procedure was successful.[40] Annex 4 also shows graphically the characteristics of the matched treated and (weighted) control groups – the close alignment of characteristics provides further comfort that, typically, the matching process has been successful.[41]

Size of treatment in successfully matched sample

As described earlier, our data on public support to innovation included not only information on which firms have been supported, but also information on the size of grants awarded to supported firms by Innovate UK and amounts received by NMS from supported firms for its research and other services.

In Table **6** below, we present, for each year in our treatment dataset, the total amounts of revenue in the original support data, compared with the total amounts in our successfully matched sample.[42]

Table 6. Innovate UK grants and NMS income included in full dataset and final analytical dataset

Year	Innovate UK funding in full support data	Innovate UK funding in matched data	NMS income in full support data	NMS income in matched data
2008	£307m	£63m	£7.0m	£0.6m
2009	£799m	£66m	£7.5m	£0.7m
2010	£707m	£94m	£8.6m	£1.2m
2011	£503m	£92m	£9.1m	£0.9m
2012	£757m	£162m	£9.5m	£1.3m

Source: Frontier Economics analysis of business support data and Business Structure Database.

[39] There are 957 tests rather than 959 after matching because in two instances all firms with a given characteristic drop out of the sample after matching, and therefore a post-matching test on that covariate could not be performed.
[40] It is not possible to test formally whether the models control for all observable characteristics which influence treatment status and outcomes. Note that while we find no examples in which the matched treatment and control groups have significant differences in turnover and employment histories, we do still sometimes see baseline differences in these measures; this leads us to carry out a difference-in-difference analysis as described earlier.
[41] The figures in Annex 4 show the *weighted* average characteristics for the matched controls (applying the matching weights derived from our estimation procedure) whereas those in this section show *unweighted* average characteristics.
[42] Matched firms in this table are treated firms used when computing the effect of treatment on employment and turnover one year after treatment.

Total Innovate UK grant funding awarded to matched treated firms varies from £63m in 2008 to £162m in 2012. This represents around 15 to 20% of the total grant funding in the full support dataset (though in 2009 only 8% of full grant income is observed in the matched dataset).

For NMS, around £1m annual income from firms is observed in the matched sample, around 10 to 15% of its total annual income in the support data.

The proportion of income observed in the analytical dataset is therefore much lower than the proportion of firms observed (see Table 5) when compared with the full support sample. This is explained by the characteristics of the matched treated. As seen in Figure **16**, organisations that were "lost" through the cleaning, trimming, and matching procedures tend to be relatively large firms, which are also likely to receive larger grants from Innovate UK or pay larger fees to NMS. For Innovate UK, for example, the top 25% grants by size account for nearly two-thirds of total grant amounts awarded between 2008 and 2012 (and nearly 90% in 2009).

Moreover, the total grant amounts reported here include a number of grant recipients that would not have been included in our analytical dataset, even before cleaning and trimming:

- Academic institutions;
- Public organisations, such as the Catapults;
- Private organisations aged less than 2 years.

Clearly, however, it is important to note that our results are not estimating the total impact of either agency's activity on employment or turnover outcomes, but that of the more limited part of their activities focused on smaller and medium-sized firms in particular.

Effects on survival

Figure 19 below shows survival effects by treatment source and firm age group. Note that the figures represent percentage point increases in survival for the treatment group compared with the matched control group.

Note that results five years after treatment are based on one treatment year only, 2008. These effects are therefore based on smaller sample sizes and the earliest treatment year in our sample (and as noted earlier the nature of the Innovate UK treatment does vary across time), so may be considered relatively less robust. However, in Annex 5 we present survival effects by age group and treatment year; there does not appear to be any 'outlier' year in which these effects are consistently larger or smaller. We also tend to see, across years, a similar pattern by which survival effects are larger for younger firms than older firms, and increase with duration since treatment.

Figure 19. Survival effect (ATT estimate), by firm age and treatment

Innovate UK

	Years following treatment				
	t+1	t+2	t+3	t+4	t+5
Survival effect: percentage points					
2 to 5	10.3%	15.3%	17.8%	19.6%	23.7%
6 to 19	5.1%	8.7%	11.9%	15.4%	16.3%
20 +	2.6%	5.0%	6.8%	8.5%	11.0%
All	*5.3%*	*8.7%*	*11.1%*	*13.9%*	*16.2%*
Standard error					
2 to 5	0.8%	1.5%	2.3%	3.1%	4.6%
6 to 19	0.4%	0.7%	0.9%	1.3%	2.2%
20 +	0.2%	0.4%	0.6%	1.0%	1.4%
All	*0.3%*	*0.5%*	*0.6%*	*0.9%*	*1.5%*
Number of treated					
2 to 5	537	365	240	167	88
6 to 19	1,240	864	593	386	166
20 +	888	631	482	285	129
All	*2,665*	*1,860*	*1,315*	*838*	*383*

NMS

	Years following treatment				
	t+1	t+2	t+3	t+4	t+5
Survival effect: percentage points					
2 to 5	14.7%	21.9%	21.1%	27.8%	32.6%
6 to 19	5.2%	8.1%	12.7%	15.2%	18.7%
20 +	2.4%	4.8%	7.0%	8.6%	13.9%
All	*5.0%*	*8.2%*	*11.3%*	*14.2%*	*18.8%*
Standard error					
2 to 5	1.1%	1.9%	4.1%	5.3%	6.6%
6 to 19	0.7%	1.3%	1.7%	2.8%	3.8%
20 +	0.5%	0.8%	1.2%	1.8%	2.9%
All	*0.4%*	*0.7%*	*1.0%*	*1.6%*	*2.3%*
Number of treated					
2 to 5	101	86	69	46	24
6 to 19	447	362	272	155	81
20 +	418	329	245	139	66
All	*966*	*777*	*586*	*340*	*171*

Significant at 5% level

Source: Frontier Economics estimates based on business support data and BSD.

The results show that support from Innovate UK or NMS has a positive, significant effect on survival probability for firms across age groups. The impact is larger for younger firms and increasing over duration since treatment. Comparing treatments, the effect appears larger for younger firms supported by NMS, but for older firms there is less evidence of any systematic difference across treatment types.

These effects show the additional percentage point increase in survival probability for treated firms compared with matched control firms. To give a sense of the size of these effects, **Figure 20** shows survival rates for control firms. Looking at the youngest firms, for example, supported by Innovate UK, after three years 70% of non-supported firms survive on average; with an ATT of almost 18% this implies nearly 90% of firms receiving support survive for at least three years. The results for the 20+ age group are particularly striking, since adding the ATT to the survival rate among control firms (recalling that this group of firms have already survived for at least 20 years) gives almost 100% survival rates for treated firms in each case.

Figure 20. Survival rates among control firms

Innovate UK

	Years following treatment				
	t+1	t+2	t+3	t+4	t+5
Survival rates among control firms					
2 to 5	87%	77%	70%	62%	55%
6 to 19	94%	88%	84%	79%	76%
20 +	97%	95%	93%	90%	88%
Average	**94%**	**88%**	**84%**	**79%**	**75%**

NMS

	Years following treatment				
	t+1	t+2	t+3	t+4	t+5
Survival rates among control firms					
2 to 5	85%	77%	70%	61%	59%
6 to 19	94%	89%	83%	77%	74%
20 +	97%	95%	91%	89%	83%
Average	**95%**	**90%**	**85%**	**80%**	**75%**

Source: Frontier Economics estimates based on business support data and BSD.

Since treatment affects survival positively, we know there will be a selection bias affecting our treatment sample. As described above, the direction of any bias in terms of estimated employment and turnover impacts is not clear; caution should therefore be attached to the key results presented below.

Effects on employment

Annex 6 and Annex 7 present some evidence that there are sometimes quite large differences in baseline employment and turnover measures between treated and control firms, despite the propensity score matching model including pre-treatment measures of size, and that we force the matching to take place within employment groups. We therefore prefer to focus on the difference-in-differences estimators as our main results.

Validity of the common trends assumption

As discussed in above, applying the difference-in-differences approach to estimate turnover and employment effects requires us to assume 'common trends' – that is, the change in outcome for non-treated firms between baseline and period t+n is assumed to be a good approximation for what would have happened to treated firms in the absence of treatment. To test this, we examined trends pre-treatment measures of turnover and employment.[43] If the common trends assumption holds, we would expect the pre-treatment trajectory of employment to be the same for treated and control groups, on average. The results are shown in Annex 4.

Briefly, we find no clear evidence of differential trends between treatment and control groups. In most cases, the trajectory between t-3 measure and t-1 (baseline) is similar for the matched treatment and control groups, on average. In cases where the trends are different, there is little evidence that the treatment or control groups are growing systematically more quickly. The one exception may be the employment effect for Innovate UK among those firms aged 6 to 19, where in each treatment year the control firms tend to be growing faster than the treatment firms; this could suggest the estimated difference-in-differences results for this group are understated, though the evidence is not particularly compelling. In general, we proceed to report the difference-in-differences results assuming that the common trends assumption holds.

[43] In particular, we look at employment and turnover outcomes in *t-2* and *t-3* for firms aged 6 to 19 and 20+ for each treatment and treatment year, applying the matching weights identified for the *t+1* outcome. We do not carry out the analysis for younger firms since not all of the group have sufficiently long pre-treatment histories of outcomes; for this age group we are relying therefore on a stronger maintained assumption that common trends holds. We do still have balancing tests for this group which find no significant differences in pre-treatment measures of employment or turnover between treated and control groups, providing further support for the common trends assumption.

Standard errors

Through the matching procedure, we can obtain as an outcome the change in turnover or employment between baseline (period 0) and outcome period (period n) for a treated $Y_n^T - Y_0^T$ or control firm $Y_n^C - Y_0^C$, and use this to estimate the standard error of the difference-in-differences estimate in levels using the following formula:

$$SE = \sqrt{\frac{1}{N}Var(Y_n^T - Y_0^T) + (\frac{1}{N^2}\sum_C w_i^2)Var(Y_n^C - Y_0^C)}$$

Where T denotes the matched treated; C denotes the matched controls; N is the total number of matched treated observations in the matching group;[44] and wi are the matching weights of each matched control observation.[45]

Deriving a standard error for the estimates in proportions is considerably more complex. The effects in proportions are obtained from the ratio:

$$\frac{\sum_{i\in T} w_i^T (Y_{in}^T - Y_{i0}^T) - \sum_{i\in C} w_i^C \left(Y_{in}^C - Y_{i0}^C\right)}{\sum_{i\in T} w_i^T\, Y_{i0}^T + \sum_{i\in C} w_i^C \left(Y_{in}^C - Y_{i0}^C\right)}$$

where the numerator and denominator are not independent. In particular, the dependency between $\sum_{i\in T} w_i^T (Y_{in}^T - Y_{i0}^T)$ and $\sum_{i\in T} w_i^T\, Y_{i0}^T$ makes it difficult to calculate the standard error of the ratio directly from the quantities obtained from the matching procedure. To take these dependencies fully into account we would have to resort to bootstrapping, which is infeasible under the computational constraints of this study.

Results

Figure 21 presents our key results, showing the difference-in-differences estimates of employment effects by source of support and firm age group. Averages across age groups are also presented.

Difference-in-differences effects are shown as the number of additional headcount employed (levels), rather than being expressed as a proportion of the estimated counterfactual.46 Further results, including the raw ATT (difference) estimates of employment impact and the baseline differences in employment between treated and control firms, are presented in Annex 6.

---

[44] That is the group within which we perform exact matching (defined by industry, size, treatment and age group).

[45] Note that the standard errors obtained by this formula are not exact (and likely to be underestimated) as they do not account for the fact that the propensity score itself (and so the matching weights) are estimates. However, obtaining correct standard errors would require bootstrapping.

[46] Recall this is the baseline employment level for treated firms plus the change in employment for control firms between baseline and the post-treatment period.

Figure 21. Difference-in-difference estimates of employment impact, by firm age and treatment

Innovate UK

	Years following treatment				
	t+1	t+2	t+3	t+4	t+5
Employment effect (difference-in-differences) - headcount					
2 to 5	1.8	2.6	2.9	5.1	2.9
6 to 19	6.0	8.3	22.1	13.5	-1.6
20 +	64.4	80.2	75.0	67.8	45.8
All	***24.8***	***32.3***	***39.0***	***31.6***	***16.8***
Standard error					
2 to 5	0.4	0.4	0.5	0.8	1.6
6 to 19	1.3	2.8	4.7	5.3	8.6
20 +	14.0	15.8	29.1	18.8	33.6
All	***4.8***	***5.7***	***11.3***	***7.2***	***12.9***
Number of treated					
2 to 5	520	336	210	136	68
6 to 19	1,223	834	565	360	152
20 +	886	626	477	279	128
All	***2,629***	***1,796***	***1,252***	***775***	***348***

NMS

	Years following treatment				
	t+1	t+2	t+3	t+4	t+5
Employment effect (difference-in-differences) - headcount					
2 to 5	0.2	0.3	1.0	1.9	-0.7
6 to 19	16.5	22.1	31.8	29.2	52.5
20 +	-5.2	25.3	13.4	13.8	40.9
All	***5.4***	***21.1***	***20.4***	***19.0***	***40.5***
Standard error					
2 to 5	0.6	0.8	1.2	2.2	3.8
6 to 19	0.9	1.4	2.2	4.0	4.4
20 +	8.5	12.0	10.0	9.6	21.7
All	***3.7***	***5.2***	***4.5***	***4.6***	***9.1***
Number of treated					
2 to 5	98	82	60	38	21
6 to 19	440	344	249	133	70
20 +	415	325	238	133	62
All	***953***	***751***	***547***	***304***	***153***

Significant at 5% level

Significant at 10% level

Source: Frontier Economics analysis based on business support data and BSD.

Both treatments have a positive effect on employment. Effects on the period 2-4 years after treatment averaged across all age groups are statistically significant.[47] For Innovate UK, employment effects are also significant within each of the age groups. For NMS, age-specific effects are only significant for the largest group – firms aged 6 to 19. Taken across firm age groups, the headcount employment effects are around 30-40 additional employed (Innovate UK) or around 20 additional (NMS). This smaller figure reflects the lower average size of firms treated by NMS compared with Innovate UK.

Expressed relative to the counterfactual outcome, these employment effects are, averaged across all firms, similar for both treatments. Focusing on the period 2-4 years after treatment, we find that treatment increases employment by around 11-14% (Innovate UK) and 12-13% (NMS).

We see little clear evidence that employment effects get larger with duration after treatment. There is also variation across treatments as to whether the larger (proportional) employment effects are found for younger firms. For Innovate UK, the effect is somewhat larger (around one-third to one-half) for younger firms aged 2 to 5, whereas for NMS the

[47] We are generally more confident in interpreting effects at this duration. It is unlikely that we would expect employment or turnover to be increased much more quickly given lags between treatment and impact. When looking at five years post-treatment, we have only a single year of treatment data (2008) to rely on and as noted above the composition of treatment for Innovate UK in 2008 is different to that observed in later years.

largest effects (around one-quarter to one-third) are seen for mid-aged firms between 6 and 19 years old.[48]

Annex 6 also shows estimates of how the proportional difference-in-differences employment impacts vary by treatment year and firm size for the two sources of treatment. We do not find any clear pattern across years; there is no year where, consistently across treatment source or age group, we see systematically higher or lower average employment effects. There is, unsurprisingly, considerably more variation in the year-specific estimates which could reflect differences in the composition of both treatment and treated from year-to-year, variation in the wider macro-economy as well as smaller year-specific sample sizes. We therefore focus largely on the estimates averaged across all treatment years.

Aggregated impact

To get a sense of the implied scale of these impacts, we took the average number of matched treated firms for each of the relevant outcome periods (2-4 years post-treatment) by treatment and multiplied by the estimated treatment effect in each year. The results suggest around 12,000 to 16,000 additional total headcount employed as a result of the Innovate UK treatment observed in our analytical dataset, and around 3,000 to 4,000 additional employed from the NMS treatment.

It is difficult to convert these additional employed into a ‘cost per job’ for a number of reasons:

- We observe treatment only for a subset of the whole support sample (see **Table 5** and **Table 6**) and it is not clear that the implied treatment effects can be extrapolated out of the sample observed;
- For NMS in particular the value of commercial spend observed is a poor measure of the cost of treatment since it is below market value and would not account for the public funds needed to develop and maintain the measurement services;
- For both treatments, firms may receive multiple episodes of support from Innovate UK or NMS.

If we take the average total grant amounts (announced rather than dispersed) by Innovate UK for the relevant treatment years (see **Table 6**) and compare to the additional headcount, the implied average cost per additional job is some £5,000. This is a crude figure (for example, it does not discount for the lag between expenditure and impact, or for any wider administration costs associated with the support schemes, or for the fact that some supported firms may be receiving multiple episodes of support). Nevertheless, the cost is low relative to other programmes,[49] in particular as the grants and services are not directly about job creation. This would suggest some caution be attached to the findings.

[48] Note that proportional impacts, averaged across all firms, are not simply averages of the proportional impact by age groups weighted by the number of treated in each age group. Rather, it is the average impact in levels expressed as a proportion of the averaged counterfactual. Given that older firms are typically considerably larger, they contribute more to the average effect across all firms.

[49] For example, Homes and Communities Agency (2015) identifies that programmes focused on job creation have indicative cost per additional job of nearer £30,000.

An alternative approach would be to use some measure of total Innovate UK spend, typically around £300 million per year, as the cost of public funds needed to provide support to firms. This would give a cost per additional job of around £18,750 to £25,000 based on 12,000 to 16,000 additional employed, though would assume that there are no additional employed as a result of firms supported by Innovate UK not captured in our final analytical sample, which would be a strong assumption.

For NMS, it is hard to derive a reasonable measure of the cost of public funds needed to support the firms observed in our final analysis as described above. The total cost of NMS activities, including publicly-funded grants, is around £70 million per year. Comparing this with 3,000 to 4,000 additional jobs would imply a cost per job (again before discounting or accounting for multiple treatment episodes) of around £18,000 to £23,000. However this again assumes that other NMS activities and support services do not yield any additional jobs which could be a strong assumption.

Effects on turnover

Validity of the common trends assumption

Annex 4 also shows the results of our inspection of pre-treatment turnover outcomes in t-3 and t-2. We find no clear evidence of differential trends between treatment and control groups: pre-baseline trajectories of average turnover are often very similar, and where there are differences there is no compelling evidence that growth rates are consistently higher for the treatment or control group. We therefore proceed to report the difference-in-differences results assuming that the common trends assumption holds.

Results

Figure 22 presents our key turnover results, showing the difference-in-differences estimates of turnover effects by source of support and firm age group. Averages across age groups are also presented. Difference-in-differences effects are shown in terms of additional turnover (levels, £ thousands). Further results, including the raw ATT (difference) estimates of turnover impact and the baseline differences in turnover between treated and control firms, are presented in Annex 7.

We find little evidence of significant turnover impacts, though the effects are usually positive. For Innovate UK, we find some evidence that at longer post-treatment durations (four and five years after treatment), averaged across all treated firms or among older firms, there are significant impacts on the level of turnover. For NMS we find only one significant effect (firms aged 6 to 19 observed two years post-treatment).

Additional turnover effects, two to four years post-treatment, are around £4.7m to £10.1m additional turnover on average (Innovate UK) or around £0.3m to £2.9m additional turnover (NMS). Expressed relative to the counterfactual outcome, the effects are (on average across all ages) larger for Innovate UK than for NMS, but typically positive for both treatments. We find that treatment increases turnover by around 12-25% (Innovate UK) and 1-11% (NMS). Translated into additional turnover, this represents

We see little clear evidence that turnover effects get larger with duration after treatment.

Figure 22. Difference-in-difference estimates of turnover impact, by firm age and treatment

Innovate UK

	Years following treatment				
	t+1	t+2	t+3	t+4	t+5
Turnover effect (difference-in-differences): £000s					
2 to 5	-7	65	34	180	-3
6 to 19	6	-178	776	2,148	2,414
20 +	14,380	16,634	25,560	10,171	10,044
All	***4,847***	***5,727***	***10,094***	***4,691***	***4,748***
Standard errors					
2 to 5	116.3	193.1	317.7	397.7	980.6
6 to 19	301.2	430.5	610.6	647.7	925.2
20 +	8,797.4	10,500.7	19,859.0	3,397.4	5,148.2
All	***2,968.2***	***3,665.7***	***7,571.3***	***1,261.5***	***1,945.7***
Number of treated					
2 to 5	520	336	210	136	68
6 to 19	1,223	834	565	360	152
20 +	886	626	477	279	128
All	***2,629***	***1,796***	***1,252***	***775***	***348***

NMS

	Years following treatment				
	t+1	t+2	t+3	t+4	t+5
Turnover effect (difference-in-differences): £000s					
2 to 5	29	20	10	-92	-151
6 to 19	454	1,067	-4	3	2,470
20 +	1,457	4,480	742	6,748	337
All	***847***	***2,430***	***322***	***2,942***	***1,246***
Standard errors					
2 to 5	260.8	200.3	762.2	1,547.3	1,193.6
6 to 19	333.7	379.9	534.0	861.8	1,517.7
20 +	3,541.6	3,059.5	3,109.9	5,136.9	4,493.3
All	***1,550.2***	***1,335.6***	***1,377.3***	***2,287.0***	***1,955.6***
Number of treated					
2 to 5	98	82	60	38	21
6 to 19	440	344	249	133	70
20 +	415	325	238	133	62
All	***953***	***751***	***547***	***304***	***153***

Significant at 5% level (Innovate UK: t+4 6 to 19, t+5 6 to 19, t+4 20+, t+4 All, t+5 All; NMS: t+2 6 to 19)

Significant at 10% level (Innovate UK: t+5 20+; NMS: t+2 All)

Source: Frontier Economics analysis based on business support data and BSD.

Annex 7 also shows estimates of how the proportional difference-in-differences turnover impacts vary by treatment year and firm size for the two sources of treatment. As with employment, we do not find any clear pattern across years; there is no year where, consistently across treatment source or age group, we see systematically higher or lower average turnover effects.

Aggregated impact

Following the approach described earlier for employment impacts, our figures suggest an aggregate additional turnover of around £2 billion to £4 billion (Innovate UK) or £60 million to £450 million (NMS) among the matched treated firms, in the 2-4 year post-treatment period.

Conclusions

We use administrative, programme level data from Innovate UK and NMS linked to firm-level performance data in the Business Structure Database to estimate the additional impact of public sector support for innovation on firm outcomes. We combine propensity score matching with difference in differences methodologies to estimate the counterfactual outcome for treated firms.

Given the need to ensure a close match between treated and non-treated firms, and difficulties inherent in applying matching methods to very large firms in knowledge-intensive sectors where most firms are treated, our results reflect the impact for largely smaller and medium-sized firms. However the method does appear to be robust for the subset of firms included in the final analysis.

Our work has highlighted the key nature of this trade-off between generalisability of the results and robustness of the matching for evaluations of firm-level interventions.

The figures also account for only a small part of the overall innovation support provided by Innovate UK and NMS. Our analysis, one of the first to adopt this methodology for the UK, suggests that using matching methods to evaluate firm-level support programmes may not be successful in general for large firms.

Summary of key findings

We find a large impact of innovation support on whether or not firms survive. Survival impacts decline with firm age. The presence of positive survival effects generates a selection bias into the impact on firm performance measured by headcount employment or turnover. This bias could be positive (if support helps successful firms overcome market failures that would otherwise have seen them exit) or negative (if support helps to prop up marginal, poorly-performing firms).

With this in mind, our results suggest that support for innovation has positive and significant impact on headcount employment, in the order of 20 (NMS) or 30-40 (IUK) additional employed two to four years after treatment. We find generally positive but not statistically significant effects on turnover over this time horizon. It could be that firms hire additional staff to support innovation as a result of receiving support, with turnover impacts taking longer to materialise, though this would require further work to uncover.

The aggregate size of our results appears relatively large given the scale of support we observe. Applying our treatment effects to the typical number of firms we observe receiving treatment in our final analytical dataset, for example, we estimate a relatively low 'cost per additional job' from the support measures included in our analysis. However, it is hard to be clear on the total cost of public funds needed to generate the aggregate impacts that we estimate, and what assumptions should be made about jobs generated outside the firms included in our final estimation. Overall, there should be a degree of caution exercised in interpreting the results: our estimates may hint that any selection effect is biasing upwards the effects on employment and turnover. However, again, confirmation of this would require further empirical study. Even if there is an upward bias in the estimates, it would require a considerable reduction in the assumed impact in order to remove the positive effects altogether. Further, our analysis does not account for any possible positive spillovers (as is common in much of the literature on innovation support).

Possible issues for further analysis

There are a number of ways in which the study could be built on.

Definition of treatment and outcome variables

Our analysis took a relatively crude measure of treatment (firms receiving support from a grant-based programme from Innovate UK or paying to use NMS services). Extensions could include:

- Relating impact to the size of grant received from Innovate UK (e.g. quantiles of the distribution of grant);
- Defining the treatment period not as the year in which an Innovate UK grant is first issued but any year in which the grant is operational;
- Splitting payments for research and non-research services for NMS;
- Investigating complementarities in treatment over time, asking whether receiving treatment leads (as an additional outcome) to increased likelihood of future treatment which could in part explain some of the large effect sizes observed for survival and employment (if firms are receiving multiple episodes of support).

Any extensions redefining treatment would require some preliminary scoping work to identify likely treatment group sizes.

It would also be possible to repeat the analysis in the future, looking at a longer time series of outcomes as more treatment years become available. This will allow for a fuller assessment of the trajectory of impacts on turnover and employment to be made and initial analysis of the impact on measures of productivity (such as turnover per employee which can be constructed from the firm-level data, though with recognition that this is a relatively crude measure of productivity). Given evidence from the literature that productivity impacts may take four or more years to realise (see Annex 2), the replication exercise could be carried out in the next two years when robust impact measures, combining multiple treatment years, should be available for up to around six years post-treatment.

Understanding the nature of the survival effect

Our work has identified the bias which could be caused by a positive impact of treatment on whether firms survive.

While in principle it could be possible to develop multi-stage structural models that try to model the impact of innovation support (selection into treatment, the impact of treatment on survival, the impact on outcomes conditional on survival), doing so in practice is likely to be extremely challenging both computationally and because of the need to identify instrumental variables which affect one stage of the process but are not relevant for other stages. It is hard to think of suitable instruments which affect selection into treatment but not other outcomes, or affect survival probabilities but not turnover or employment conditional on survival. One possibility may be to exploit exogenous variation in policy parameters (such as eligibility criteria) should they exist, though this would not allow for a general evaluation of the impact of support from a range of policies.

More pragmatically, it would be possible to 'bound' the potential survival effects. Within an age group, we know the additional probability of survival that results from treatment. Suppose for example that treatment is estimated to improve survival by ten percentage points. We can take all treated firms and rank by performance (measured by change in turnover or employment between treatment and outcome period). We can then remove the top and bottom performing firms from the treated group until the number of remaining treated matches the predicted number that would have survived without treatment, and recomputed the treatment effects on the remaining treated. If the additional survivors are all the best or worst performers, we would then have a rough bound on the likely survival effect.

Note that implementing this requires two key maintained assumptions. First, we need to assume that while some firms who would otherwise have died are able to survive as a result of treatment, the reverse is not true: that is, there are no firms which die as a result of treatment which otherwise would have survived. It is easy to posit cases where this would note hold: for example, where receipt of support for innovation enables firms to take more risks.

We also need to assume that the change in outcome after treatment for a given firm is a reasonable way to rank the impact of treatment. However we do not identify the counterfactual (no treatment) outcome for any individual firm.

However as a first step in establishing the potential scale of the survival effects, maintaining the assumptions above may be reasonable.

Alternative ways to deal with selection on unobservables

Our employment and turnover effects suggest large aggregate impacts. This could be driven by selection effects resulting from survival. It could also result from some residual problem with selection on unobservables (which in turn could partly explain the impacts on survival): firms that seek and receive support for innovation are those that, for reasons not related to observable characteristics, perform better. We attempted to control for this as fully as possible by including past support and past performance in our specification. However this may not fully capture the issue. Other approaches could include:

Using alternative datasets such as the Annual Business Survey which include more firm-level demographics (but trade off sample size) to try a more fully specified propensity score model. This would need a scoping exercise to understand the relevant trade-offs.

Limiting the control group so that only firms which are ‘innovative’ (e.g. those observed in BERD, or those who are interacting with the public sector in less intensive ways such as being on databases or receiving advisory services) can be matched with treated firms. This may require building in more information from public sector administrative sources.

Bibliography

Aguiar, L. and P. Gagnepain (2012), European Cooperative R&D and Firm Performance, Universidad Carlos III de Madrid Working Paper 12-07 (http://e-archivo.uc3m.es/bitstream/handle/10016/13749/we1207.pdf?sequence=1)

Becker, B. (2015), 'Public R&D Policies and Private R&D Investment: a Survey of the Empirical Evidence', Journal of Economic Surveys, 29 (5), 917–42

Benanvente, J., G. Crespi and A. Maffioli (2007), Public Support to Firm-Level Innovation: An Evaluation of the FONTEC Program, Office of Evaluation and Oversight Research Paper 05/07, Washington, DC: IADB (www10.iadb.org/intal/intalcdi/PE/2013/11564.pdf)

BEIS (2014), Estimating The Effect Of UK Direct Public Support For Innovation, BEIS Analysis Paper Number 04 (www.gov.uk/government/uploads/system/uploads/attachment_data/file/369650/bis-14-1168-estimating-the-effect-of-uk-direct-public-support-for-innovation-bis-analysis-paper-number-04.pdf)

Cannone, G. and E. Ughetto (2012), 'Funding Innovation and Regional Level: An Analysis of a Public Policy Intervention in the Piedmont Region', Regional Studies, 48(2), 270–83

Colombo, M., L. Grilli and S. Murtinu (2011), 'R&D Subsidies and the Performance of High-Tech Start-Ups', Economics Letters, 112, 97–9

Cerulli, G. and Potì, B. (2012), 'Evaluating the robustness of the effect of public subsidies on firms' R&D: An application to Italy', Journal of Applied Economics, 15, 287–320

Corrado, C., et al. (2005), 'Measuring Capital and Technology: An Expanded Framework', in Corrado, C., J. Haltiwanger and D. Sichel (eds.), Measuring Capital in the New Economy, Chicago: The University of Chicago Press

Danish Agency for Science, Technology and Innovation (2011), Economic Impact of International Research and Innovation Cooperation: Analysis of 25 Years of Danish Participation in EUREKA, Copenhagen: Danish Agency for Science, Technology and Innovation (www.eurekanetwork.org/sites/default/files/publications/25-years-danish-participation-eureka-annual.pdf)

Du, J., Y. Gong and Y. Temouri (2014), High Growth Firms and Productivity – Evidence from the United Kingdom, Nesta Working Paper 13/04 (www.nesta.org.uk/sites/default/files/high_growth_firms_and_productivity_-_evidence_from_the_united_kingdom.pdf)

Duch, N., D. Montolio and M. Mediavilla (2009), 'Evaluating the Impact of Public Subsidies on a Firm's Performance: a Two-Stage Quasi-Experimental Approach', Investigaciones Regionales, 16, 143–65

Frontier Economics (2014), Rates of Return to Investment in Science and Innovation, Department for Business, Energy and Industrial Strategy (www.gov.uk/government/uploads/system/uploads/attachment_data/file/333006/bis-14-990-rates-of-return-to-investment-in-science-and-innovation-revised-final-report.pdf)

Görg, H. and E. Strobl (2007), 'The effect of R&D subsidies on private R&D', Economica, 74, 215–34

Griffith, R., E. Huergo, J. Mairesse and B. Peters (2006), 'Innovation and productivity across four European countries', Oxford Review of Economic Policy, 22 (4), 483-98

Griliches, Z. and F. R. Lichtenberg (1984), 'R&D and Productivity Growth At the Industry Level: Is There Still a Relationship?', in Griliches, Z. (ed.), R&D, Patents, and Productivity, Chicago, Illinois: Chicago University Press

Guellec, D. and B. Van Pottelsberghe de la Potterie (2003), 'The impact of public R&D expenditure on business R&D', Economics of Innovation and New Technology, 12, 225–43

Hall, B.H., F. Lotti J. and Mairesse (2009), 'Innovations and productivity in SMEs: Empirical evidence for Italy', Small Business Economics, 33(1), 13-33

Hanel, P. (2000), 'R&D, inter-industry and international technology spillovers and the total factor productivity growth of manufacturing industries in Canada, 1974–1989', Economic Systems Research, 12(3), 345–61

Haskel, J. and G. Wallis (2010), Public Support for Innovation, Intangible Investment and Productivity Growth in the UK Market Sector, IZA Discussion Paper No. 4772, Institute for the Study of Labor (http://ftp.iza.org/dp4772.pdf)

Haskel, J. and G. Wallis (2013), 'Public support for innovation, intangible investment and productivity growth in the UK market sector', Economics Letters, 119(2), 195-98

Homes and Communities Agency (2015), Calculating Cost Per Job: Best Practice Note (www.nwueu.ac.uk/NWUEU/LatestUpdates/PDF/CPJ%20BPN%20%202015%203rd%20Edition%20-%20Final.pdf)

Kaiser, U. and J. Kuhn (2012), Long Run Effects of Public-Private Research Joint Ventures: The Case of the Danish Innovation Consortia Support Scheme, IZA Discussion Paper 5986 (http://ftp.iza.org/dp5986.pdf)

Nishimura, J. and H. Okamuro (2011), 'Subsidy and Networking: The Effects of Direct and Indirect Support Programs of the Cluster Policy', Research Policy, 40(5), 714–27

OECD (2014), Science, Technology and Industry Outlook 2012, available at www.oecd-ilibrary.org/science-and-technology/oecd-science-technology-and-industry-outlook-2012_sti_outlook-2012-en

PACEC (2011), Evaluation of the Collaborative Research and Development Programmes: Final Report, London: Technology Strategy Board (http://webarchive.nationalarchives.gov.uk/20130221185318/http:/www.innovateuk.org/_assets/pacec_evaluation_of_crandd_report_final260911%20(2).pdf)

Regeneris Consulting Ltd. (2010), Knowledge Transfer Partnerships Strategic Review, London: Technology Strategy Board (http://webarchive.nationalarchives.gov.uk/20140827133341/http:/www.innovateuk.org/_assets/pdf/corporate-publications/ktp%20strategic%20review%20feb%202010.pdf)

Roper, S. and N. Hewitt-Dundas (2014), ‘Knowledge Stocks, Knowledge Flows and Innovation: Evidence from Matched Patents and Innovation Panel Data’, Research Policy, 44(7), 1327–40

Rosenbaum, P. and D. Rubin (1983), ‘The central role of the propensity score in observational studies for causal effects’, Biometrika, 70(1), S.1–55

Ruegg, R. and I. Feller (2003), A Toolkit for Evaluating Public R&D Investment Models, Methods, and Findings from ATP's First Decade, Gaithersburg: National Institute of Standards and Technology

Salter, A.J. and B. R. Martin (2001), ‘The economic benefits of publicly funded basic research: a critical review’, Research Policy 30(3), 509-532

Sissoko, A. (2014), R&D Subsidies and Firm-Level Productivity: Evidence from France, Working Paper (www.gredeg.cnrs.fr/Documents%5C2014%5CSissoko_2014.pdf)

SQW (2002), Evaluation of the Teaching Company Scheme: Report to Small Business Service, DTI Evaluation Report Series, No. 7

SQW, Cambridge Econometrics and BMG Research (2015), Evaluation of Smart: Impact and Process Evaluation, London: Innovate UK (www.gov.uk/government/uploads/system/uploads/attachment_data/file/467204/Smart_Evaluation_-_Final_Final_Report_7_October.pdf)

Technopolis (2014), The Case for Public Support of Innovation at the Sector, Technology and Challenge Area Levels, London: BEIS (www.gov.uk/government/uploads/system/uploads/attachment_data/file/334369/BIS_14_852_The_Case_for_Public_Support_of_Innovation.pdf)

What Works Centre for Local Growth (2015), Evidence Review 9 – Innovation: Grants, Loans and Subsidies, London: What Works Centre for Local Growth (www.whatworksgrowth.org/public/files/Policy_Reviews/15-10-20-Innovation-Grants-Loans-Subsidies-Report.pdf)

Annex 1: Public support for innovation

Funding of private innovation through grants

UK businesses have historically had access to public resources for their innovation activities through programmes funded by the Department for Business, Energy and Industrial Strategy (BEIS) and predecessors. These programmes are now largely administered through Innovate UK,[50] a non-departmental body supported by BEIS. Other departments also offer funding opportunities for innovation with the potential to benefit society. For example, the former-Department for Energy and Climate Change (DECC) has allocated £25 million in funding between 2012 and 2013 through the Energy Entrepreneurs' Fund (EEF) to support the development and demonstration of innovative technologies and processes in energy efficiency, power generation and energy storage.

Government funding for innovation may have an effect on economic activity (Haskel and Wallis, 2013), though it is possible that much government-funded R&D (particularly that funded outside of BEIS) is aimed less at promoting business activity than other wider social benefits including health and national security (Frontier Economics, 2014).

Key historical programmes provided under DTI/BEIS/Innovate UK include:[51]

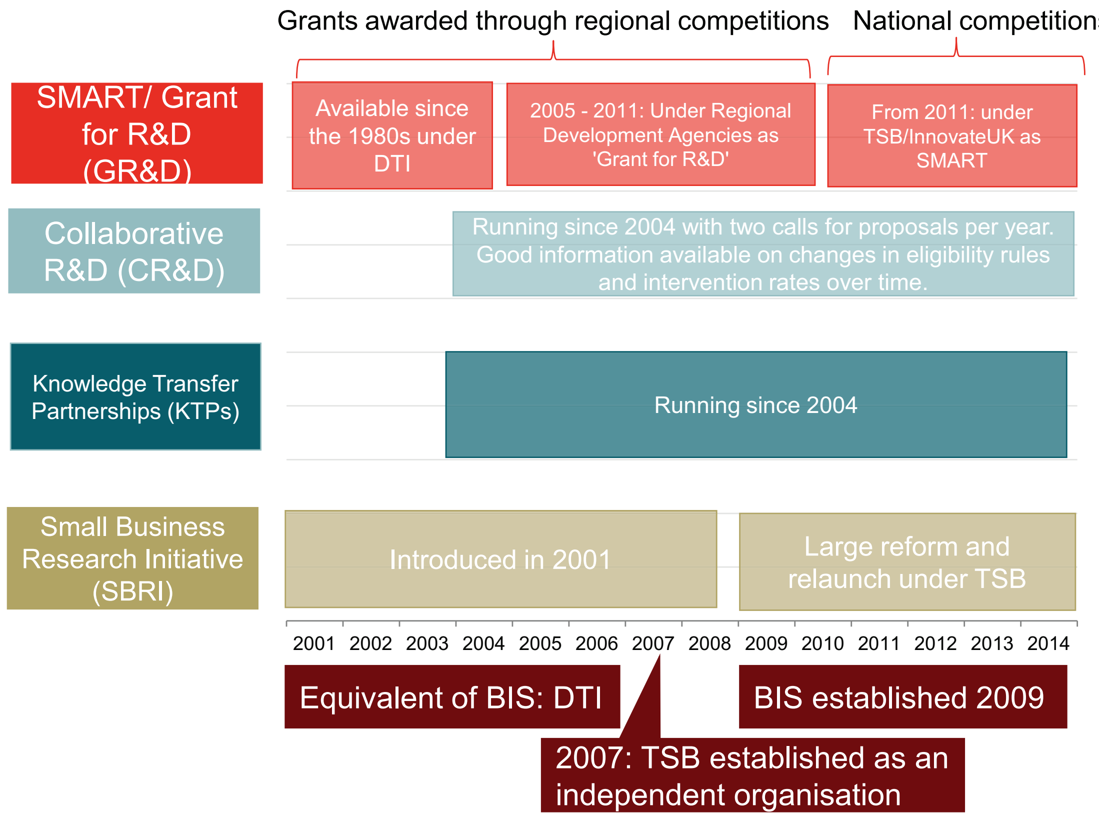
- Smart (previously also known as Grant for R&D): grant funding made available to micro enterprises and Small and Medium Enterprises (SMEs) on a competitive basis, not restricted to specific themes or industries.
- Collaborative R&D: grant funding for businesses, universities, and research and technology organisations to work collaboratively on innovative projects. Eligible projects aim to tackle specific technical or societal challenges identified in funding competitions run by Innovate UK.
- Knowledge Transfer Partnerships (KTPs): grant funding to cover part of a business' research partners' cost. KTPs then aim not only to provide funding for private research, but also to support businesses in accessing specialised knowledge. This programme was established in 2004, building on the previous Teaching Company Scheme (TCS). While TCS was largely restricted to two-year projects, KTPs are flexible between one and three years. Within KTPs, businesses are also free to choose among a wider base of partners, including for example Further Education colleges as well as Higher Education institutions.
- Small Business Research Initiative (SBRI): helping businesses to develop an innovative product or service through a contract, typically worth up to £1 million, from a public sector organisation needing a solution to a specific challenge. This

[50] Previously known as the Technology Strategy Board (TSB).
[51] Sources: Innovate UK website and historical snapshots of the Technology Strategy Board website available through the UK Government Web Archive; European Commission Erawatch UK country reports 2008-2013; Innovation policy 'toolset manual' provided by Innovate UK.

programme also aims to encourage the adoption of innovations in the public sector. The SBRI therefore supports private innovation not only through the direct provision of funding, but also by stimulating demand for innovation.

Figure 23 below provides an overview of the introduction and evolution of these programmes over time.

Figure 23. Key programmes under the responsibility of Innovate UK



Source: Frontier Economics analysis of Innovate UK material and of the European Commission's annual Erawatch UK country reports.

Firms in specific industries considered of strategic importance by the UK Government may also benefit from public funding for innovation activities through other channels. For example, in 2013, the UK Government announced a commitment of £2 billion funding for the development of aerospace technology to be provided jointly with the aerospace industry over a seven-year period.

Access to finance

Recent programmes aimed at helping businesses access private funding for research and innovation include:

- The Enterprise Finance Guarantee (introduced in 2009 and taking over from the Small Firms Loan Guarantee, introduced in 1981): government guarantee for up to 75% of qualifying loans of amounts up to £1 million.
- The Enterprise Capital Funds: government co-funding with private sector funds targeting investments of up to £2 million in SMEs. The first five funds were launched between 2006 and 2007.

Advice and access to knowledge and facilities

UK businesses can access knowledge and facilities required for their innovation activities through a number of institutions:[52]

- Catapults, a network of technology and innovation centres designed to increase the UK's capacity to commercialise research;
- Innovation and Knowledge Centres (IKCs), which offer a shared environment for academia and business to work on commercial applications of emerging technologies. IKCs also offer grant funding for projects responding to thematic calls, jointly with Research Councils.
- The National Physical Laboratory (NPL), the national measurement standards laboratory for the United Kingdom. NPL provides training and on-line resources through its website; cooperation in research activities; measurement services; contract research and consultancy services.
- The Intellectual Property Office (IPO). The IPO provides resources and advice on intellectual property issues through regional Patent Information Centres and other services including the IPO online health check and funding intellectual property audits for innovative firms.
- The Manufacturing Advisory Service, now part of the Business Growth Service, providing coaching, consultancy, mentoring, advice on access to finance and export activities to business with the potential to grow.

[52] UK Trade and Investment (UKTI) provides a number of services specifically targeted to innovative firms, including for example the Venture Capital Unit, which aims to link innovative SMEs with overseas sources of early equity investment, or the UKTI Life Sciences Organisations, which helps UK life sciences companies to do business overseas, and encourages foreign life science companies to invest in the UK. However, these services are generally not aimed specifically at supporting innovation but rather provide support to businesses that have innovated or that act in innovative industries.

Annex 2: Evidence on outcome additionality

Table 7. Literature using firm-level data to identify impact of innovation support on economic outcomes

Study	Country	Approach	Key results
Sissoko (2014)	France	Impact of EUREKA, providing support for formation of Research Joint Ventures. Uses difference-in-difference together with matching methods, linking programme administration data with Amadeus data of firm performance.	Treated firms see positive increase in TFP of about 18% compared with control firms at around 4 years post-treatment. The effect is larger for firms which are initially less productive. No significant effects on employment, physical capital or average wage.
Aguiar and Gagnepain (2012)	EU	Impact of Research Joint Ventures. Use IV estimation to account for endogeneity of selection into RJV. Use industry-level funding availability as an instrument for participation.	Labour productivity rises 40% after 3-4 years. Profit margin increases by 4-5 percentage points.
Kaiser and Kuhn (2012)	Denmark	Impact of Research Joint Ventures. Difference-in-difference estimation on a matched dataset (using nearest neighbour matching).	One year after participation, number of employees increases by 0.03%. Effect is larger for patent-active firms and after a longer delay. No significant impact on value-added or labour productivity.
Cannone and Ughetto (2012)	Italy	Evaluates impact of European Structural Funds used to stimulate innovation in Piedmont, including grants. Use data on applicants matched with administrative data on firm outcomes, with a matching and difference-in-difference approach.	Positive, significant impact on sales up to 3 years post-treatment though not for all components of the policy. No impact on profitability.
Colombo et al. (2011)	Italy	Sample of new tech startups. Data from a survey in 2004 including history of public support received. Use IV to account for endogenous treatment; instruments are total public subsidy/variation in treatment approach.	Competitively allocated R&D subsidies increase TFP by just over 30%. With no competitive allocation, there is no impact. Note the lag time from treatment to TFP impact is not clear from the study.

Study	Country	Approach	Key results
Nishimura and Okamuro (2011)	Japan	Impact of participation in Industrial Cluster Project, involving 'hard' support (direct R&D funding) and 'soft' support (support for networking/collaboration). Matching and selection methods comparing survey-based outcomes for participants with non-participants.	R&D subsidies have positive, significant effect on sales transactions. Softer support (helping collaboration with other businesses, financial institutions, technological advice and financial advice) also has positive significant effect. Outcomes observed 1-3 years post treatment.
Danish Agency for Science, Technology and Innovation (2011)	Denmark	Analysis of EUREKA, providing financial and other support for innovation. 76 participating businesses are compared with control firms who are not in any scheme or are in other schemes, using matching and difference-in-difference methods and drawing on firm-level admin data.	Labour productivity growth was more than twice as fast for participants than non-participants three years after treatment, but growth was similar compared with participants in other schemes. Significant positive effect on exports only after three years (compared with both control samples), not at other post-participation lags. Significant positive effect on turnover only after four years compared with non-participants, no significant effect at any other lag. Positive significant effect on employment 1-6 years post-treatment compared with other scheme control group; positive effect only at 1-2 years compared with non-participants.
Duch et al. (2009)	Spain	Evaluate Catalan scheme providing R&D subsidies on firm value-added. Use matching method to identify control group from firm-level administrative data, and regression analysis on the matched sample.	Value added grows 10-13 percentage points more quickly over two years for firms receiving a subsidy.
Benavente et al. (2007)	Chile	Evaluation of FONTEC, financing projects supporting product and process innovation. Uses matching and difference in difference methods drawing on recall survey data of participants and non-participants. Outcomes identified only one year after programme participation.	Positive, weakly significant (10% level) effects on sales (in percentage terms), employment (in levels) and probability of exporting. Positive but not significant effects on sales levels, employment (percentage terms) and labour productivity.

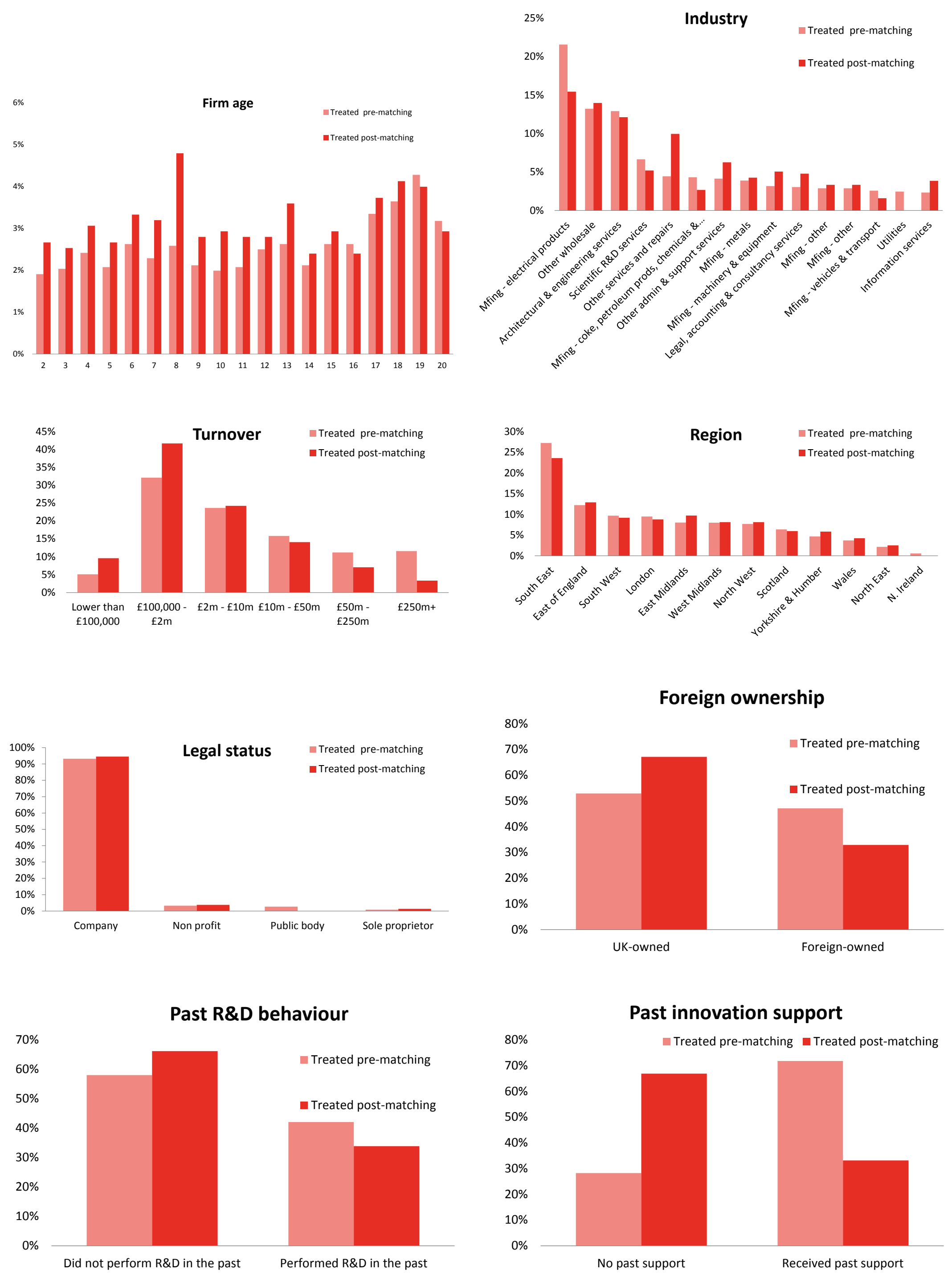
Source: Frontier Economics, drawing on What Works Centre for Local Growth (2015).

Annex 3: Pre- and post-matching sample

Figure 24. Distribution of covariates among treated firms by matching status, Innovate UK

Source: Frontier Economics analysis based on business support data and BSD.

Figure 25. Distribution of covariates among treated firms by matching status, NMS

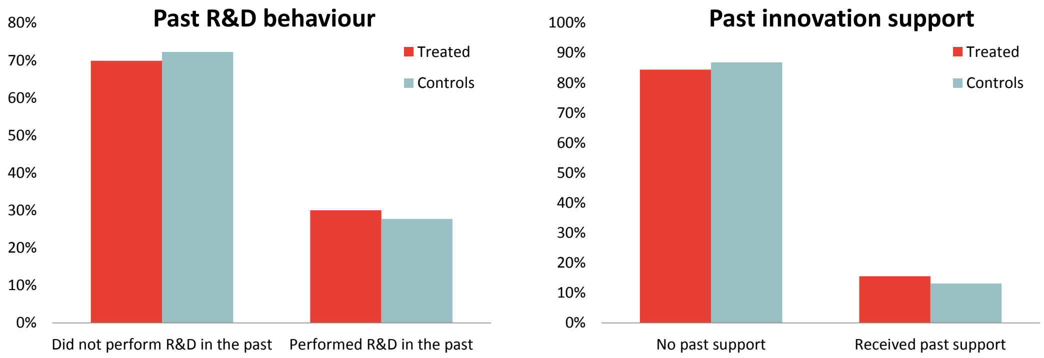


Source: Frontier Economics analysis based on business support data and BSD.

Annex 4: Validity of approach

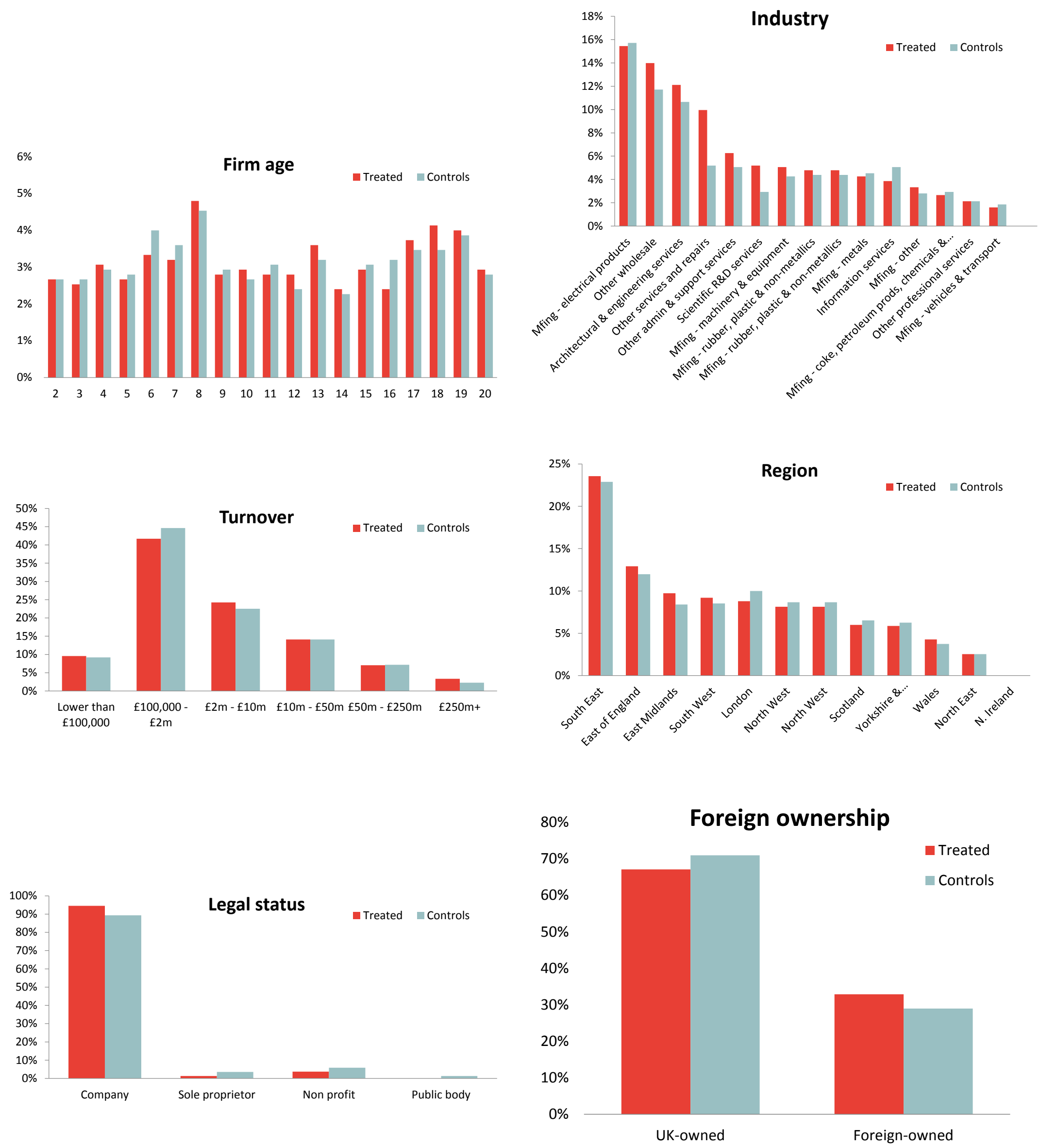
Comparison of treated and control firm characteristics

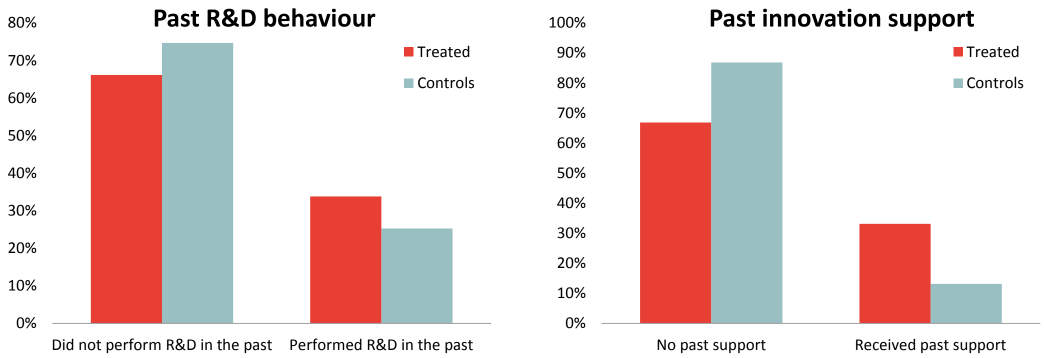
Figure 26. Distribution of covariates among matched treated and control firms, Innovate UK



Source: Frontier Economics analysis based on business support data and BSD. Figures are weighted averages using matching weights derived from the estimation procedure.

Figure 27. Distribution of covariates among matched treated and control firms, NMS

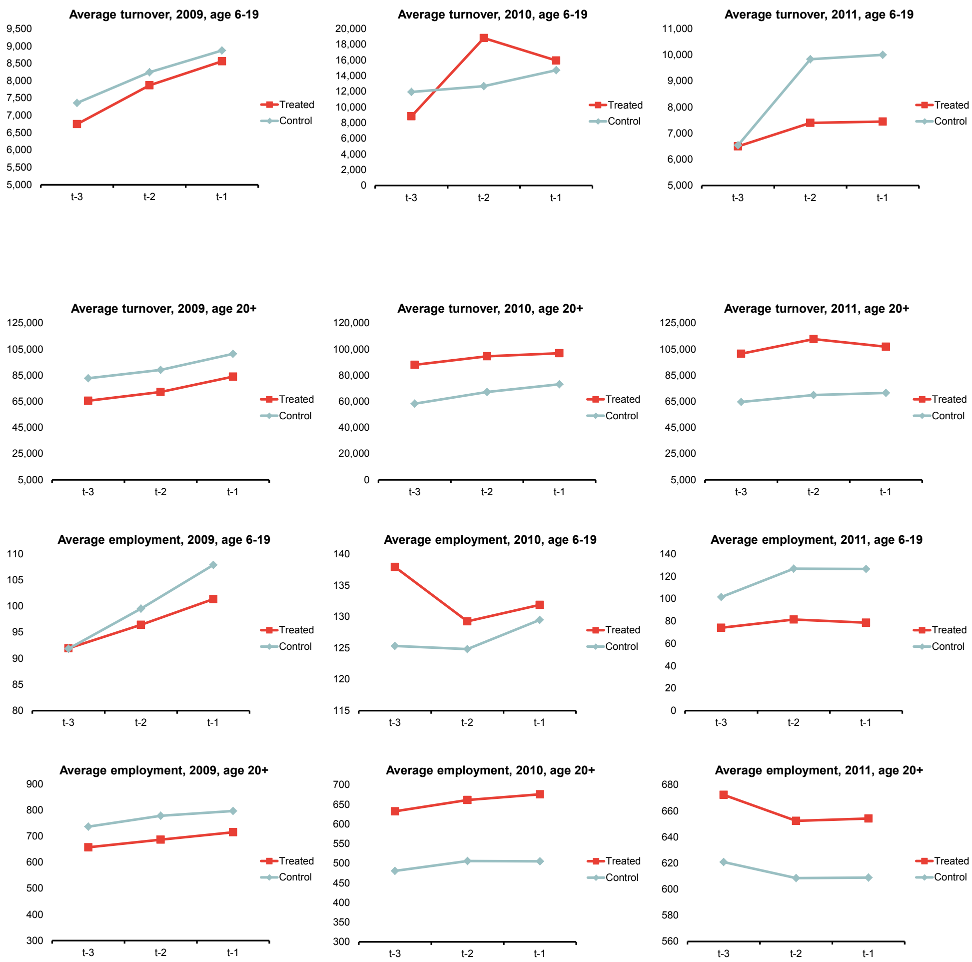




Source: Frontier Economics analysis based on business support data and BSD. Figures are weighted averages using matching weights derived from the estimation procedure.

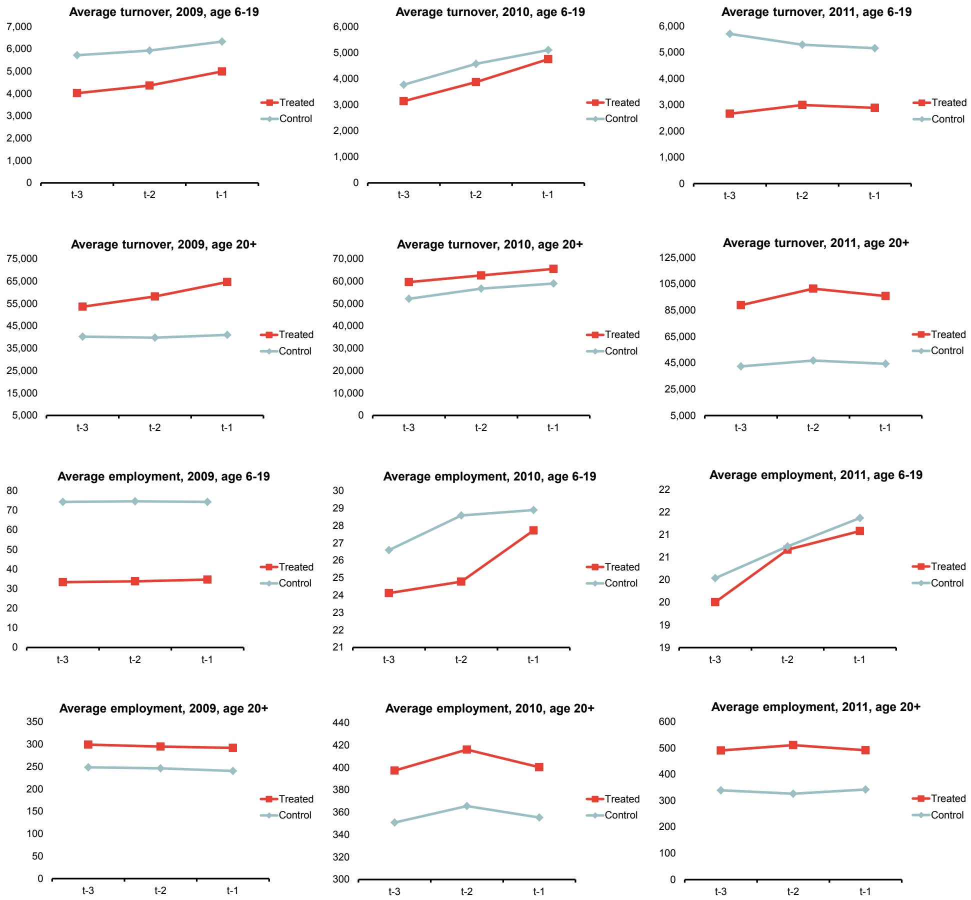
Pre-treatment trends in outcomes of interest

Figure 28. Pre-treatment trends – Innovate UK (by age and treatment year)



Source: Frontier Economics analysis based on business support data and BSD.

Figure 29. Pre-treatment trends – NMS (by age and treatment year)



Source: Frontier Economics analysis based on business support data and BSD.

Annex 5: Detailed results – survival effects

Figure 30. Survival effects, by age group and treatment year, Innovate UK

Age group	Treatment year	Years following treatment t+1	t+2	t+3	t+4	t+5
2 to 5	2008	**12.1%**	**15.6%**	**20.3%**	**20.9%**	**22.5%**
2 to 5	2009	**7.3%**	**13.1%**	**19.5%**	**16.0%**	
2 to 5	2010	**9.6%**	**14.0%**	**11.9%**		
2 to 5	2011	**11.6%**	**15.7%**			
2 to 5	2012	**9.5%**				
6 to 19	2008	**5.6%**	**8.6%**	**10.9%**	**13.8%**	**16.6%**
6 to 19	2009	**5.9%**	**11.2%**	**14.3%**	**16.6%**	
6 to 19	2010	**3.5%**	**5.7%**	**10.0%**		
6 to 19	2011	**4.4%**	**8.7%**			
6 to 19	2012	**5.6%**				
20+	2008	**3.0%**	**4.7%**	**6.9%**	**8.6%**	**10.5%**
20+	2009	**2.4%**	**4.9%**	**5.8%**	**7.8%**	
20+	2010	**2.0%**	**4.5%**	**6.6%**		
20+	2011	**3.0%**	**5.1%**			
20+	2012	**2.5%**				

Source: Frontier Economics analysis from the business support data and BSD. Note: Figures in bold red type are statistically significant at the 5% level. Results are percentage point impacts.

Figure 31. Survival effects, by age group and treatment year, NMS

Age group	Treatment year	Years following treatment t+1	t+2	t+3	t+4	t+5
2 to 5	2008	**11.0%**	**12.6%**	**15.6%**	**20.7%**	**24.4%**
2 to 5	2009	**18.9%**	**24.9%**	**22.6%**	**23.0%**	
2 to 5	2010	**8.4%**	**13.8%**	10.8%		
2 to 5	2011	**12.9%**	**18.7%**			
2 to 5	2012	**6.9%**				
6 to 19	2008	**6.3%**	**11.2%**	**13.1%**	**14.7%**	**17.4%**
6 to 19	2009	**5.7%**	6.4%	**11.0%**	**14.3%**	
6 to 19	2010	**5.6%**	**7.9%**	**12.7%**		
6 to 19	2011	2.3%	**5.8%**			
6 to 19	2012	**5.5%**				
20+	2008	3.2%	**6.1%**	**6.8%**	**8.7%**	**12.3%**
20+	2009	2.2%	2.8%	**6.0%**	**8.1%**	
20+	2010	**2.7%**	**5.1%**	**7.0%**		
20+	2011	1.0%	2.8%			
20+	2012	1.5%				

Source: Frontier Economics analysis from the business support data and BSD. Note: Figures in bold red type are statistically significant at the 5% level. Results are percentage point impacts.

Annex 6: Detailed results – employment effects

Figure 32. Further employment impacts, by firm age and treatment

Innovate UK

	Years following treatment				
	t+1	t+2	t+3	t+4	t+5
Average employment among control firms					
2 to 5	6.8	7.7	8.4	9.6	10.5
6 to 19	107.3	140.9	144.6	146.9	195.9
20 +	582.6	582.7	576.7	638.2	543.2
Difference at baseline (treated - control)					
2 to 5	0.0	0.0	0.2	0.1	-0.1
6 to 19	-8.2	-13.8	2.4	-10.9	-16.7
20 +	95.6	49.7	51.9	-25.0	40.8
Impact on level of employment (ATT)					
2 to 5	1.8	2.6	3.1	5.2	2.9
6 to 19	-2.2	-5.5	24.4	2.6	-18.2
20 +	160.0	129.9	126.9	42.8	86.7
Proportional impact on employment (ATT)					
2 to 5	26.8%	33.2%	37.2%	53.5%	27.3%
6 to 19	-2.0%	-3.9%	16.9%	1.8%	-9.3%
20 +	27.5%	22.3%	22.0%	6.7%	16.0%
Standard error of proportional impact (ATT)					
2 to 5	7.0%	11.3%	16.6%	85.6%	44.4%
6 to 19	8.6%	12.9%	12.5%	18.3%	40.7%
20 +	8.0%	6.5%	7.5%	7.5%	12.6%
Employment effect (difference-in-differences) - level					
2 to 5	1.8	2.6	2.9	5.1	2.9
6 to 19	6.0	8.3	22.1	13.5	-1.6
20 +	64.4	80.2	75.0	67.8	45.8
Standard error of difference-in-differences level effect					
2 to 5	0.4	0.4	0.5	0.8	1.6
6 to 19	1.3	2.8	4.7	5.3	8.6
20 +	14.0	15.8	29.1	18.8	33.6

NMS

	Years following treatment				
	t+1	t+2	t+3	t+4	t+5
Average employment among control firms					
2 to 5	9.0	8.7	9.9	11.8	14.8
6 to 19	68.7	81.3	96.7	127.6	145.1
20 +	302.7	319.3	312.8	262.0	297.6
Difference at baseline (treated - control)					
2 to 5	-0.3	-0.1	-0.1	-0.2	-0.3
6 to 19	-23.9	-33.1	-46.3	-56.6	-62.6
20 +	84.9	47.7	23.9	11.5	-22.3
Impact on level of employment (ATT)					
2 to 5	-0.1	0.2	0.9	1.7	-1.0
6 to 19	-7.4	-11.0	-14.5	-27.4	-10.1
20 +	79.8	72.9	37.4	25.3	18.6
Proportional impact on employment					
2 to 5	-1.4%	2.3%	9.6%	14.1%	-7.0%
6 to 19	-10.7%	-13.5%	-15.0%	-21.5%	-7.0%
20 +	26.3%	22.8%	11.9%	9.7%	6.3%
Standard error of proportional impact					
2 to 5	12.8%	18.2%	22.9%	44.3%	46.0%
6 to 19	5.5%	7.5%	31.3%	22.8%	22.5%
20 +	5.2%	6.1%	7.5%	17.6%	11.5%
Employment effect (difference-in-differences) - level					
2 to 5	0.2	0.3	1.0	1.9	-0.7
6 to 19	16.5	22.1	31.8	29.2	52.5
20 +	-5.2	25.3	13.4	13.8	40.9
Standard error of difference-in-differences level effect					
2 to 5	0.6	0.8	1.2	2.2	3.8
6 to 19	0.9	1.4	2.2	4.0	4.4
20 +	8.5	12.0	10.0	9.6	21.7

Significant at 5% level

Significant at 10% level

Source: Frontier Economics analysis of business support data and BSD. Note: Employment defined as number of employees including owner.

Figure 33. Difference-in-differences estimates of employment effect (proportional), by firm age and treatment year, Innovate UK

Age	Year	*t+1*	*t+2*	*t+3*	*t+4*	*t+5*
2 to 5	2008	32.8%	24.7%	26.7%	29.9%	27.8%
2 to 5	2009	20.1%	39.6%	54.0%	77.8%	
2 to 5	2010	15.9%	22.2%	20.6%		
2 to 5	2011	40.1%	41.6%			
2 to 5	2012	20.8%				
6 to 19	2008	4.6%	2.2%	9.9%	10.1%	-0.8%
6 to 19	2009	3.1%	4.9%	10.6%	8.2%	
6 to 19	2010	16.3%	17.8%	25.8%		
6 to 19	2011	0.4%	0.9%			
6 to 19	2012	5.3%				
20 +	2008	10.5%	8.0%	7.5%	4.4%	8.4%
20 +	2009	10.4%	12.5%	13.2%	14.6%	
20 +	2010	-1.0%	7.5%	16.6%		
20 +	2011	16.0%	27.0%			
20 +	2012	17.1%				

Source: Frontier Economics analysis of business support data and BSD. Note: standard errors not available so no significance shown.

Figure 34. Difference-in-differences estimates of employment effect (proportional), by firm age and treatment year, NMS

Age	Year	*t+1*	*t+2*	*t+3*	*t+4*	*t+5*
2 to 5	2008	0.8%	7.3%	4.3%	1.2%	-4.9%
2 to 5	2009	-0.8%	-2.8%	-5.1%	38.2%	
2 to 5	2010	15.9%	2.8%	31.1%		
2 to 5	2011	7.1%	6.8%			
2 to 5	2012	-7.3%				
6 to 19	2008	24.3%	26.4%	30.1%	27.6%	36.2%
6 to 19	2009	10.3%	13.4%	12.9%	15.0%	
6 to 19	2010	55.7%	52.1%	53.2%		
6 to 19	2011	-1.5%	2.7%			
6 to 19	2012	-1.3%				
20 +	2008	3.2%	8.4%	9.0%	4.7%	13.7%
20 +	2009	4.4%	10.5%	10.3%	5.9%	
20 +	2010	0.2%	13.6%	-0.6%		
20 +	2011	4.9%	-2.1%			
20 +	2012	-24.0%				

Source: Frontier Economics analysis of business support data and BSD. Note: standard errors not available so no significance shown.

Annex 7: Detailed results – turnover effects

Figure 35. Further turnover impacts, by firm age and treatment

Innovate UK

	Years following treatment t+1	t+2	t+3	t+4	t+5
Average turnover among control firms (£000s)					
2 to 5	677	736	912	1,180	1,385
6 to 19	10,901	15,455	16,584	16,616	24,615
20 +	80,238	85,330	87,682	90,562	68,451
Difference at baseline (treated - control, £000s)					
2 to 5	-50	-42	-54	-92	-129
6 to 19	-481	-1,655	-1,199	-3,520	-7,749
20 +	20,943	17,146	11,197	3,514	28,717
Impact on level of turnover (ATT): £000s					
2 to 5	-56	22	-19	87	-132
6 to 19	-475	-1,833	-423	-1,372	-5,335
20 +	35,322	33,780	36,757	13,685	38,761
Proportional impact on turnover (ATT)					
2 to 5	-8.3%	3.0%	-2.1%	7.4%	-9.5%
6 to 19	-4.4%	-11.9%	-2.5%	-8.3%	-21.7%
20 +	44.0%	39.6%	41.9%	15.1%	56.6%
Standard error of proportional impact (ATT)					
2 to 5	21.0%	43.8%	44.7%	85.2%	140.6%
6 to 19	34.1%	15.7%	96.0%	302.8%	233.7%
20 +	52.0%	255.0%	77.2%	117.5%	47.5%
Turnover effect (difference-in-differences) - £000s					
2 to 5	-7	65	34	180	-3
6 to 19	6	-178	776	2,148	2,414
20 +	14,380	16,634	25,560	10,171	10,044
Standard error of difference-in-differences level effect					
2 to 5	116	193	318	398	981
6 to 19	301	430	611	648	925
20 +	8,797	10,501	19,859	3,397	5,148

NMS

	Years following treatment t+1	t+2	t+3	t+4	t+5
Average turnover among control firms (£000s)					
2 to 5	916	906	1,127	1,554	3,058
6 to 19	8,883	10,024	11,736	17,188	24,954
20 +	53,915	59,190	63,083	54,702	62,244
Difference at baseline (treated - control, £000s)					
2 to 5	53	67	136	92	36
6 to 19	-1,732	-2,235	-2,226	-4,059	-6,789
20 +	19,683	17,922	6,018	10,068	-2,266
Impact on level of turnover (ATT): £000s					
2 to 5	-56	22	-19	87	-132
6 to 19	-475	-1,833	-423	-1,372	-5,335
20 +	35,322	33,780	36,757	13,685	38,761
Proportional impact on turnover (ATT)					
2 to 5	9.0%	9.6%	13.0%	0.0%	-3.8%
6 to 19	-14.4%	-11.6%	-19.0%	-23.6%	-17.3%
20 +	39.2%	37.8%	10.7%	30.7%	-3.1%
Standard error of proportional impact (ATT)					
2 to 5	75.1%	19.6%	112.7%	57.4%	72.1%
6 to 19	80.3%	78.6%	8894.7%	95.5%	185.6%
20 +	19.8%	194.5%	16.5%	70.9%	40.3%
Turnover effect (difference-in-differences) - £000s					
2 to 5	29	20	10	-92	-151
6 to 19	454	1,067	-4	3	2,470
20 +	1,457	4,480	742	6,748	337
Standard error of difference-in-differences level effect					
2 to 5	261	200	762	1,547	1,194
6 to 19	334	380	534	862	1,518
20 +	3,542	3,060	3,110	5,137	4,493

Significant at 5% level

Significant at 10% level

Source: Frontier Economics analysis of business support data and BSD. Note: turnover measured in £000s.

Figure 36. Difference-in-differences estimates of turnover effect (proportional), by firm age and treatment year, Innovate UK

Age	Year	*t+1*	*t+2*	*t+3*	*t+4*	*t+5*
2 to 5	2008	12.0%	15.5%	5.0%	1.2%	-0.2%
2 to 5	2009	-3.3%	1.7%	12.6%	29.3%	
2 to 5	2010	-4.3%	27.1%	-12.6%		
2 to 5	2011	23.0%	0.9%			
2 to 5	2012	-17.1%				
6 to 19	2008	4.7%	-18.8%	-3.4%	12.0%	9.8%
6 to 19	2009	2.9%	0.5%	11.4%	14.3%	
6 to 19	2010	10.5%	28.6%	9.1%		
6 to 19	2011	-9.6%	-8.8%			
6 to 19	2012	-12.5%				
20 +	2008	11.7%	-11.7%	-3.9%	18.8%	14.7%
20 +	2009	-3.1%	0.2%	5.1%	7.4%	
20 +	2010	5.1%	-5.5%	68.7%		
20 +	2011	7.3%	4.0%			
20 +	2012	50.6%				

Source: Frontier Economics analysis of business support data and BSD. Note: standard errors not available so no significance shown.

Figure 37. Difference-in-differences estimates of turnover effect (proportional), by firm age and treatment year, NMS

Age	Year	*t+1*	*t+2*	*t+3*	*t+4*	*t+5*
2 to 5	2008	-1.9%	4.9%	-1.4%	-3.7%	-5.0%
2 to 5	2009	-2.1%	-10.8%	-21.3%	-10.2%	
2 to 5	2010	14.0%	15.3%	20.4%		
2 to 5	2011	-0.2%	-1.0%			
2 to 5	2012	5.9%				
6 to 19	2008	-1.0%	3.9%	2.3%	-2.7%	9.9%
6 to 19	2009	1.7%	14.9%	11.5%	9.6%	
6 to 19	2010	6.5%	3.1%	-12.5%		
6 to 19	2011	17.6%	25.8%			
6 to 19	2012	5.0%				
20 +	2008	4.6%	-18.0%	-4.1%	15.9%	0.5%
20 +	2009	-10.6%	11.7%	13.8%	8.4%	
20 +	2010	6.9%	10.3%	-2.1%		
20 +	2011	17.6%	26.1%			
20 +	2012	-9.1%				

Source: Frontier Economics analysis of business support data and BSD. Note: standard errors not available so no significance shown.

This publication is available from: www.gov.uk/beis

Contacts us if you have any enquiries about this publication, including requests for alternative formats, at: enquiries@beis.gov.uk