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Asymmetric information and heterogeneous effects of R&D subsidies: Evidence on R&D investment and employment of R&D personel*

Mehmet Ugur (University of Greenwich)

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1. Introduction

Business investment in research and development (R&D) may remain below optimum due to knowledge externalities (Arrow, 1962; 1996; Romer, 1990) and/or capital market failures in pricing risky R&D projects correctly (Bloom et al., 2007; Czarnitzki and Toole, 2007; Minton and Schrand, 1999). However, there are also arguments that the gap between the *socially-optimal* and *actual* levels of R&D investment may be small for several reasons. First, firms need to invest in R&D and build "absorptive capacity" in the first place to benefit from knowledge externalities (Cohen and Levinthal, 1989; Hottenrott and Peters, 2012; Griffith et al., 2004). Second, the extent of knowledge spillovers can be limited by patent protection and commercial secrecy (Nadiri, 1993). Finally, public subsidies may even lead to excess R&D investment if competition unfolds as 'patent races' (Dasgupta and Stiglitz, 1980; Dasgupta, 1988; Fudenberg et al., 1983).

These competing theoretical perspectives suggest that the gap between the firms' actual and optimal levels of R&D investment before the subsidy is likely to be heterogeneous. To the extent this is the case, the effect of an optimal subsidy from the funder's point of view is likely to generate heterogeneous R&D efforts. Indeed, this is evident in a recent meta-analysis of the empirical literature, which reports that the effects vary considerably between primary studies and more than 40% of the reported estimates indicate either crowding-out effects or no effect (Dimos and Pugh, 2016).

A handful of studies have reported within-study heterogeneity too. For example, Guellec and Van Pottelsberghe de la Potterie (2003), and Gorg and Strobl (2007) report a hump-shaped relationship between the effect size and the the ratio of subsidy to R&D investment (subsidy intensity), with higher probability of crowding-out effects at the low and high ends of the support intensity distribution. Czarnitzki and Toole (2007) report that the additionality effect is smaller as product-market uncertainty increases. There is also evidence that the additonality effect is larger among firms receiving support from multiple sources (Czarnitzki and Lopes-Bento, 2013). Hud and Hussinger (2015), on the other hand, find that the subsidy is associated with a crowding-out effect during the financial crisis year of 2009, in contrast to additionality effects in other years. Finally, Marino *et al.* (2016) find that R&D tax credits may amplify the crowding-out effects of the subsidies.

The empirical literature, however, has offered little theoretical explanation for effect-size heterogeneity. Explanations tend to be *ex post* and even then the relationship between the heterogeneous findings and information asymmetry in a principal-agent setting is often overlooked. We aim to bridge this gap by drawing on the theory of contracts; and demonstrate that the treatment effect heterogeneity is related to levels of informational rents that different firm types can extract when the subsidy contract is characterised by asymmetric information, risk aversion and non-verifiability of the state of nature.

The theory of contracts is well-documented (Laffont and Mortimort, 2009; Hart and Moore, 1990; Hart, 2017) and has been applied widely in research on regulation and organisation (Mookherjee, 2006). A recent study by Akcigit *et al.* (2017) extends the application of mechanism design in the context of public support for business R&D. Drawing on this work, we demonstrate that the subsidy-induced incentives differ between firm types and propose four hypotheses on how a subsidy that satisfies the incentive constraints of the participating firms generate different treatment effects.

First, we hypothesize that subsidies would be associated with crowding-out (substitution) effects after the onset of financial crises. This is due to tighter liquidity/credit constraints and lower expected profits from R&D, which induce the risk-averse firms to reduce effort or require insurance against risk at each level of the subsidy set by the funder. Secondly, we hypothesize that subsidies are more likely to be associated with additionality (complementarity) effects among younger firms and start-ups, but with crowding-out effects among older firms. Our third hypothesis concerns firm size and can be stated as follows: subsidies are more likely to be associated with additionality effects among smaller firms, but with crowding-out effects among larger firms. Finally, we hypothesize that the relationship between R&D intensity and the treatment effect has an inverted-U shape. In the latter three hypotheses, type-dependent effect-size heterogeneity is due to different levels of informational rents that firms can extract, depending on their efficiency with which they can convert the R&D input into quality innovations/products.

We test these hypotheses using propensity score matching (PSM) and double robust (DR) estimators applied to an unbalanced panel dataset of 43,650 R&D-active UK firms from 1998-2012. We provide a range of estimation results based on: (i) pooled data for the full period; (ii) two sub-periods (1998-2007 and 2008-2012); (iii) pooled data for different firm-types in terms of age, size and R&D intensity; and (iv) cross-section data for each year in the analysed period. One of our findings is that UK public subsidies have been associated with crowding-out effects in the aftermath of the *dot.com* bubble (2003-2004) and after the global financial crisis (2009-2012) [1]. Secondly, subsidies are associated with crowding-out effects among larger and older firms. In contrast, subsidies are associated with additionality effects when the firm is a start-up, young or small. Overall, the average treatment effect on the treated (ATT) in the whole period or in any particular year decays monotonously when regressed on age or size deciles. Finally, we find that the ATT follows an inverted-U pattern when evaluated against the firm's privately-funded or total R&D intensity. These findings are consistent across two estimators and hold for two innovation inputs: privately-funded R&D intensity and the ratio of R&D personnel to total employment.

The rest of the paper is organised as follows. In section 2, we review the relevant literature to demonstrate why an *ex ante* theoretical framework is required to explain heterogeneity in the subsidy's effects on business R&D investment. Section 3 discusses the funding regime in the UK, spells out the information asymmetries it entails, and draws on contract theory to distil testable hypotheses about the sources of heterogeneity in the treatment effect. In section 4, we present our dataset and empirical strategy. Here we first provide evidence on the treated and untreated samples, the coverage rate (the percentage of firms in receipt of government subsidy), the support intensity (the ratio of subsidy to privately-funded R&D expenditures), and the distribution of the public subsidy by firm age and size. Then we discuss the PSM and DR estimators and how we address the issues that arise in the context of pooled panel data. The empirical results are presented in section 5, followed with additional sensitivity and matching quality checks in the Appendix. Finally, in the conclusions, we distil the main findings and discuss their implications for future research and public policy.

[1] The start of the dot.com and global financial crises are 2001 and 2007, respectively. However, the trough for both are 2002 and 2009 respectively.

2. Relevant literature

Following the pioneering work by Blank and Stigler (1957), a growing number of researchers have utilised a variety of datasets and different estimation methods to establish whether public support for business R&D has complementary or substitution effects. David *et al*. (2000) review the evidence mainly from structural models without control for selection into treatment. Of 14 firm-level studies reviewed, three reported additionality, five studies based on US data reported crowding-out effects, and the remaining six reported mixed findings. The findings are similar in later reviews, of which Garcia-Quevedo (2004) reviews 28 studies that utilize firm-level data and reports that seven studies find additionality, ten studies find no significant effects, and eleven report crowding-out effects. A recent meta-analysis of the evidence from 52 primary studies published from 2000-2013 demonstrates that the *meta-average* of the partial correlation coefficient is small in two-thirds of the estimations and moderate in the rest. Also, about 40% of the findings indicate crowding-out or insignificant effects; whereas the remaining 60% indicate additionality effects (Dimos and Pugh, 2016).

Another empirical pattern is that studies based on continental European data and more recent studies that utilise matching methods tend to report additionality effects more often than previous studies. For example, Hall and Maffioli (2008) report additionality effects from development funds sponsored by the World Bank in Latin America. Similarly, Czatrnitzki and Lopes-Bento (2013) report additionality effects in Flanders, using the fourth Community Innovation Survey data and matching difference-in-difference (D-i-D) estimator. Other studies reporting similar effects include Czarnitzki and Hussinger (2004) and Hussinger (2008) for German firms; Duguet (2004) for French firms; and Aerts and Schmidt (2008) for firms in Germany and Flanders.

However, the estimates are heterogeneous even among recent studies and those based on European data. For example, Czarnitzki and Toole (2007) report smaller additionality effects as product-market uncertainty increases. Czarnitzki and Lopes-Bento (2013) acknowledge that it is necessary to verify if the treatment effect is time-varying, particularly during crisis years. This is done in Hud and Hussinger (2015), who report that subsidies are associated with a crowding-out effect during the crisis year of 2009.[2] Takalo *et al.*, (2013) report that the treatment effect is positive on average but the latter conceals a high degree of heterogeneity among Finnish firms. Finally, Marino et al. (2016) investigate the effect of subsidies on private R&D expenditure in a sample of French firms from 1993–2009 and report that crowding-out effects are stronger under the R&D tax-credit regime and among recipients of large and medium-sized subsidy doses compared to recipients of lower doses or non-subsidised firms.

Although we observe increased attention to effect-size heterogeneity, the explanation for the latter is usually *ex post* or has nothing to say about whether it may be reflecting different levels of informational rents that firms may extract under the subsidy contract. To our knowledge, only two studies have so far offered *ex ante* theoretical explanations for the heterogeneous firm responses to public subsidy.

Wanzenböck *et al.,* (2013) focus on three types of behavioural additionality (project, scale and cooperation additionality) and identify three firm characteristics as potential determinants: R&D intensity/experience, technological specialization, and collaboration propensity. Their findings indicate that R&D-intensive firms are less likely to exhibit behavioural additionality because such firms have the capacity and the experience to identify and realise the desired R&D projects irrespective of public support.

On the other hand, Lee (2011) focuses on input additionality and utilizes a model that identifies four potential channels through which public support can influence business R&D investment: (i) the technological-competence-enhancing effect; (ii) the demand-creating effect; (iii) the R&D-cost-reducing effect; and (iv) the project overlap (or duplication) effect. Their findings indicate that public support is associated with crowding-out effects among large firms, but with additionality effects among small and financially-constrained firms. The crowding-out effect among large firms are explained by their proximity to the technological frontier, which leaves little need for catching up. In contrast, additionality effects among small firms are explained by these firms' distance to the frontier and their eagerness to catch up.

[2] Effect-size heterogeneity is also observed in studies that investigate the effect of tax rebates on private R&D investment. For example, Baghana and Mohnen (2009) estimate the price elasticity of R&D investment with respect to tax credits among Canadian firms and report that: (i) while short-run additionality effects are observed among small firms, the effect is insignificant among large firms; and (ii) the long-run additionality effect decays over time, but the decay is more pronounced among large firms.

These studies represent welcome steps in the right direction, but they overlook the agency costs that may arise under the subsidy regime, the extent of information asymmetries between the principal (the funder) and the agent (the subsidized firm), and the ways in which information asymmetries may induce different firm types to respond to subsidies differently. To address these issues, we draw on insights from the contract theory and its implications for public policy design (Laffont and Tirole, 1986; Baron and Myerson, 1982; Sappington, 1982; Bolton and Dewatripont, 2005). In the next section, we summarise the subsidy regime in the UK and demonstrate why the agency problems inherent in the regime can be analysed effectively by drawing on insights from the contract theory. In the second part, we develop four testable hypotheses informed by contract theory.

3. The funding regime and agency costs: Testable hypotheses

Direct support for business R&D is provided by the UK government departments and their agencies; and non-departmental public bodies such as the *Technology Strategy Board* and its successor, *Innovate UK*.[3] Despite this fragmented outlook, two main features of the regime stand out. First, the largest part of the direct funding has been managed by non-departmental agencies, of which *Innovate UK* is the current incumbent. The latter provides funding for business-led projects with the objective of stimulating R&D and innovation activity.

Secondly, UK support for business R&D has to comply with the *State-Aid* rules of the European Union (EU), under which R&D grants should not lead to unfair competition in the product market. The risk of unfair product-market competition is measured by the proximity of the applicant's project to its market operations – the so-called market readiness level (MRL). R&D activities that score 1 or 2 on the RML scale are furthest away from the market. They consist of basic research and qualify for public funding of up to 100% (see Table 1). Activities with an MRL score of 3 to 6 are considered as conducive to product and process innovations that may not be undertaken optimally due to spill-over effects or market imperfections. Part-funding for such activities account for the largest part of the UK (and EU) R&D subsidies.

[3] The non-departmental public agencies also include eight regional development agencies (RDAs), which also provided R&D funding from 2000 to 2012, but then discontinued.

Table 1: Funding rates as percentage of eligible project costs – Innovate UK: 2014

Project type→ **Firm size↓**	Fundamental research	Feasibility studies	Industrial research	Experimental development
Micro (<10 employees) or Small (<50 employees)	100%	70%	60%	35%
Medium (<250 employees)	100%	60%	60%	35%
Large (250+ employees)	100%	50%	50%	25%

Source: Innovate UK.

To secure public funding, the applicant must satisfy a number of selection criteria, including: (i) whether the project could be undertaken without public funding; (ii) how the project represents value for money for the taxpayer; and (iii) how the applicant will benefit from the innovation, including the latter's impact on productivity and growth. The additionality requirement is made explicit on the application form, which requires the applicant to explain why public support is sought and why private finance may not be available for the project.[4]

If a subsidy is granted, the *Innovate UK* monitors funded projects against detailed project plans and financial forecasts. Payments to successful applicants are made for project-related costs *incurred* and *paid* between the project start and end dates, and in quarterly arrears. This set up implies that the firm's planned R&D investment is observable and hence no information asymmetries are involved with respect to this indicator. However, information asymmetry *does* exist with respect to two unobservable factors: the firm's research effort (the diligence with which the firm converts the R&D inputs into quality innovations); and its research productivity (the efficiency with which the firm converts the unobservable effort and the observable R&D expenditures into innovative products). In addition, the *Innovation UK,* like many other public R&D funders, does not monitor the firm's output or its price-cost margin.

This funding regime constitutes a typical principal-agent setting, where the principal (funder) concludes a contract with the agent (firm) with a view to induce the latter to undertake R&D investment that would not have been possible without public support. The behavioural assumptions in this setting are: (i) the principal and the agent are rational and both try to maximize their utilities; (ii) the agent has private information about its type in terms of effort

[4] See Innovate UK, *Short Guidebook for Innovate UK Competition Applicants* at *https://sbri.innovateuk.org/documents/17078356/21883504/Innovate%20UK%20Guidebook_FINALDIGITALVERSION.pdf?version=1.0*

and efficiency; (iii) the principal does not know the agent's type, but the probability distribution of the agent types is common knowledge; and (iv) the principal moves first by offering a contract under asymmetric information about the agent’s type, while the agent accepts or declines the contract.

Under perfect information where firm-types in terms of research effort and research productivity are fully observable, the funder will be able to set the optimal subsidy that maximise social welfare. In turn, the firm would respond to the subsidy by increasing its privately-funded R&D investment because the latter’s marginal cost is lower after the subsidy. This first-best outcome does not preclude effect-size heterogeneity due to different levels of knowledge spillovers faced by heterogeneous firms. However, and to the extent that knowledge spillovers exist, effect-size heterogeneity would be revealed as a variation in the magnitude of the additionality effects rather than as a mixture of additionality and crowding-out effects as reported in the literature.

Under asymmetric information, the first-best outcomes are not feasible as both the subsidy and R&D investment allocations must satisfy the incentive constraints of the firms that differ in terms of unobservable research effort and research productivity. Departures from the first-best outcomes reflect informational rents (or agency costs) that arise when firms conceal their true types in terms of effort, efficiency and risk-aversion, which are known to the firm but only their distribution is common knowledge (Akcigit et al., 2017: 16; Laffont and Mortimort, 2009: 50; Salanie, 2005).

In what follows, we define four key concepts that underpin our hypotheses on sources of heterogeneity in the subsidy’s effect on business R&D investment. The first is *incompleteness of the R&D subsidy contract*. The subsidy contract is incomplete in that it neither defines all possible states of nature that may affect the parties’ performance, nor does it provide for an adjudicator that would settle disputes between the parties. Incomplete contracting is due to high cost of writing *ex ante* contracts contingent on every state of nature (Laffont and Mortimort, 2009: 231). Furthermore, verifying the contractual performance is quite difficult when the agent “makes representations that the true state of the world is different than both parties know it to be.” (Williamson, 1975: 32). In Laffont and Mortimort (2009), such sources of contention are conducive to second-best agent performance if the agent is risk averse.

The second concept is *firm efficiency* in converting the observable R&D expenditures and the unobservable research effort into quality products. As demonstrated in recent studies (Bloom et al., 2007; Bloom *et al.*, 2013), variation in firm efficiency may reflect heterogeneity in management practices; or it can be a function of firm characteristics such as age, size, R&D intensity that affect firm efficiency in converting the R&D input into quality innovations/products (Akcigit *et al.*, 2017). Under information asymmetry, more efficient firms can extract information rents by concealing their 'true type' and mimicking low-efficiency firms. Both the theory of contracts (Laffont and Martimort, 2009) and its application to mechanism design in the context of public support for R&D investment (Akcigit *et al*., 2017) demonstrate that the incentive-compatible subsidy and the firms' R&D investment are second-best under asymmetric information about the firm's research efficiency (productivity). Also, the second-best outcomes entail informational rents that the efficient firm-types are able to extract by mimicking inefficient firms. Akcigit *et al.*, (2017) further demonstrate that: (i) the incentives to conceal one's type are higher if the firm is more risk-averse and more efficient; and (ii) the informational rents are higher when the funder does not monitor the firm's output.

The third is *R&D investment wedge*, which measures the deviation of the optimum level of R&D investment after subsidy from the level of R&D investment that the firm would choose with patent protection only. This wedge provides an indicator about the level at which the optimal subsidy should be set, taking account of two corrections that address market failures and one modification due to information asymmetry: (i) a Pigouvian correction for spillovers from the firm's own innovation; (ii) a "monopoly quality valuation correction" that would induce the firm to equalise its marginal private benefits of the product quality improvement with marginal social benefits; and (iii) a modification to the first-best incentive, designed to satisfy the incentive constraint of the efficient firm. The larger the R&D investment wedge is the higher are the incentives for R&D investment (Akcigit et al. 2017).

The fourth concept is the *relative complementarities* of the observed R&D investment to the firm's unobserved research effort and research productivity. In Akcigit et al. (2017), the firm can extract a higher level of informational rents if the complementarity of its R&D investment to research productivity is higher than the complementarity to research effort.

Our first hypothesis (**H1**) relates to the effect of financial crises on the behaviour of subsidized firms. We assume that the probability distribution of the crisis and non-crisis periods in the economy is common knowledge, but neither the funder nor the subsidy-recipient is certain about which state will be observed when the contract is implemented. Also, the parties do not contract on how the financial crisis might affect firm performance. This is apparent from the absence of a third party (a court of justice) that would resolve conflicts and enforce the contract when disputes arise about how the change in the state of nature affects the parties' payoffs. In this setting, the effect of a crisis on the subsidized firm's response to the subsidy depends on two key parameters: the degree of the firm's risk-aversion and the extent to which the firm's observed R&D investment becomes a noisy indicator of performance.

In both Laffont and Martimort (2009) and Akcigit *et al.* (2017), risk-aversion and noise in the firm's observed performance indicator (which is R&D investment in our case) are associated with *more inefficient* allocations of the subsidy and R&D investment. On the one hand, the onset of a financial crisis increases the risks faced by risk-averse firms and induces the latter to reduce effort at each level of subsidy offered. Reduced effort, in turn, will lead to lower R&D investment as the subsidy on offer does not provide sufficient insurance against increased risks. On the other hand, the funder will be less able to hold the firm to account on the basis of observed R&D investment, as the latter becomes a "noisy" indicator of the unobserved research effort. The "noise" is due to increased variance of the privately-funded R&D investment, which is a function of the cost and availability of the external finance after the crisis.

Laffont and Mortimort (2009: 253, 271) demonstrate that *ex ante* non-verifiability does not entail agency costs if an adjudicator exists and the latter "…can credibly impose punishments" on the party that violates the contract. In the absence of such a 'court of justice', however, the combination of risk aversion and reduced quality of the observed R&D investment as an indicator of effort causes departures from the first-best allocations. Given this theoretical conclusion, we state our first hypothesis (**H1**) as follows:

> **H1: R&D subsidies will be associated with crowding-out or smaller additionality effects after the onset of a financial crisis due to increased risk aversion and contestability of the R&D performance as an indicator of true firm effort.**

An increase in perceived risks during economic downturns can be inferred from the analysis in Akcigit et al., (2017), whose model depends on interest rate, program horizon, R&D costs, mean sales growth, and median R&D expenditures to sales. As firms' survival time and growth of sales are smaller after the onset of a financial crisis, the model predicts weaker firm responses to subsidies. Findings in other studies also point out in the same direction. In Acemoglu and Linn (2005) and Dubois *et al*. (2015), pharmaceutical firms reduce R&D investment during downturns as the latter reduce the market size, which is a major determinant for innovation incentives. Furthermore, Bloom (2007) demonstrates that the firm's R&D effort during periods of uncertainty becomes less responsive to public subsidies and sales. Finally, the average R&D investment is lower as sales volatility increases, and this negative association is stronger among credit-constrained firms (Aghion et al., 2012).

Our second and third hypotheses relate to why the treatment effect may depend on firm type in terms of age and size, respectively. Akcigit *et al.* (2017) demonstrate that, under asymmetric information, the firm's R&D investment wedge is determined by exogeneous characteristics that determine the firm type. Specifically, the authors find that the R&D investment wedge: (i) declines monotonically with firm age; (ii) follows a hump-shape pattern as the firm type becomes increasingly efficient; and (iii) is smaller if the funder does not control the firm's output (i.e., if the funder takes the intellectual property protection regime as given).

Akcigit *et al.*, (2017: 29-30) point out that the time horizon for the R&D (or any) investment is shorter as the firm gets older and the firm's duration is finite with a known expected value. An increase in firm age, therefore, is associated with a lower level of R&D investment under *laissez-faire* or with *subsidy*. This is because R&D investment contributes to firm's value for a smaller number of periods as the firm gets older and the time horizon for its investment gets shorter.

However, there may be a direct age effect in that the firm's efficiency in converting R&D inputs into quality products may also change with age. A large body of work on firm dynamics report that age is positively correlated with firm survival; and that younger firms have a higher probability of exiting, but those that survive tend to grow faster than average (Geroski, 1995; Ugur *et al.*, 2016a). This is usually explained by learning with age: older firms are more efficient in converting the R&D investment into quality products compared to younger firms, but may also be less adaptive to disruption due to organizational inertia (Hannan and Freeman, 1989). Given this association between age and R&D efficiency, older (hence more efficient) firms have incentives to conceal their true types and extract informational rents. Therefore, we state our second testable hypothesis (**H2**) as follows:

H2: R&D subsidies will be associated with crowding-out or smaller additionality effects when the firms are older, but an additionality effect is more likely when the firm is younger or a start-up.

In studies of industry evolution and growth, firm age and size are positively correlated (Haltiwanger et al., 2013; Akcigit and Kerr, 2010; and Aghion et al., 2014; 2015). In our data, the correlation between the logarithms of firm age and size is 0.51 and highly significant. Given this correlation, it is empirically plausible that the incentives of the firm to invest in R&D with or without subsidy may be falling in firm size, just as it does fall with firm age under Hypothesis 2. This is because older firms are likely to be larger too.

Although this empirical explanation is plausible, we argue that there is also a theoretical reason as to why firm responses to subsidies would be size-dependent too. For example, Audretsch and Mahmood (1995), Dunne *et al.* (1988) and Mata and Portugal (1994) report that the positive correlations between firm size and survival is due to the accumulation of basic competitive assets and skills, both of which increase with firm size. In the Schumpeterian work, firm size is measured by the number of product lines that reflect the rate of success in the firm's innovation history. A firm must have succeeded in introducing new product lines before it survives and becomes large and tend to grow faster than average (Aghion et al., 2014; 2015).

Given these insights, we argue that a larger firm size (in terms of employment or turnover) is an indicator of more efficient firm type. From the perspective of contract theory, the R&D investment wedge among larger (hence more R&D-efficient) firms is smaller with or without subsidy. Therefore, the treatment effect of public subsidy on larger firms can be expected to be smaller than that of smaller firms. Hence, we state our third hypothesis (H3) as follows:

H3: R&D subsidies will be associated with crowding-out or smaller additionality effects when the firms are larger; but an additionality effect is more likely when the firms are smaller.

H2 and **H3** also in line with other insights from the incomplete contracts literature, which focuses on the hold-up problem (Hart and Moore, 1990; Hart, 2017). Under incomplete contracting, the hold-up problem is conducive to underinvestment irrespective of whether the principal or the agent is the residual claimant for total (private and social) returns to investment. If the funder were the residual claimant, under-investment would occur because the agent would get only part of the *ex post* gains from trade. If the firm were the residual claimant, under-investment would occur because of the risks that the firm would face. The evidence in Table 3 below indicates that a relatively smaller number of large and old firms account for disproportionately higher proportions of the subsidies and R&D investment. This fact motivates the larger and older firms to mimic smaller and younger firms that typically are more risk-averse.

Our fourth hypothesis concerns the relationship between the treatment effect and the firm's R&D intensity. To flesh out this hypothesis, we draw on a key parameter in Akcigit *et al.* (2017): the *complementarity* of R&D investment to research effort compared to research productivity. When the complementarity of the R&D investment to research productivity is relatively larger than the complementarity with research effort, the firm would be closer to the optimal level of R&D investment without subsidy. Therefore it would require a larger subsidy to increase R&D investment from a level that is close to the optimum (Akcigit *et al.*, 2017). Therefore, the optimal subsidy from the funder's perspective would be associated with smaller treatment effects when the increase in the firm's R&D intensity contributes more to the firm's research productivity than to its research effort.

In contrast, an increase in the firm's R&D intensity will be associated with larger treatment effects if the firm's R&D investment is more complementary to its research effort. This is because, the increase in R&D intensity will induce the firm to exercise higher research effort. This is clearly preferable for the funder, who would match the increased effort with a larger subsidy (Akcigit et al., 2017: 4, 16). Therefore, for a given subsidy, the treatment effect will be larger when the firm's R&D intensity increases and the increase in the latter is more complementary to the firm's research effort.

The question is whether we can establish the levels of R&D intensity at which R&D investment is more complementary to research productivity compared to research effort (or vice versa). Akcigit et al. (2017) provide part of the answer: the complementarity of the R&D investment to research productivity dominates the complementarity to the research effort when the firm is efficient – i.e., when it is more productive in converting the R&D input into quality products. The other part can be deduced from Schumpeterian models of innovation and growth, which demonstrate that R&D investment is a stronger determinant of productivity as the firm is nearer to the technology frontier – i.e., when its R&D intensity is high (Aghion *et al.*, 2014; 2015).

Therefore, we conclude that the complementarity of the R&D investment to research productivity would dominate the complementarity to research effort at relatively high levels of R&D intensity. In contrast, the complementarity of the R&D investment to research effort would dominate at relatively low levels of R&D intensity. Given this conclusion, we can state our fourth hypothesis (**H4**) as follows:

> **H4: The treatment effect will follow an inverted-U pattern when evaluated against R&D intensity: the effect increases as R&D intensity rises from a low level, but gradually declines and may become negative as R&D intensity increases beyond a certain threshold.**

In the following sections, we test these hypotheses using two treatment effect estimators (PSM and DR) on a random panel sample of 43,650 R&D-active UK firms from 1998 to 2012. We evaluate the effect of subsidy on two innovation inputs: the ratio of privately-funded R&D expenditures to turnover and the share of R&D personnel (scientists and technicians) in total employment.

4. Data and methodology

Data

Our dataset is from the Business Research and Development Database (BERD) – a repeated annual survey designed to measure R&D expenditures by UK businesses.[5] The BERD survey is based on a sample of R&D-active firms, stratified by product group and employment size-bands. The R&D-active status is established on the basis of information from the R&D Tax Credit claims, community innovation surveys (CIS), responses to a survey question about R&D activity in the Annual Business Survey (ABS), and other sources of administrative data. The stratified sample consists of large (size-band1) firms with 400+ employees (sampled 1:1); size-band2-firms (100-399 employees) sampled 1:5 and size-band3-firms (0-99 employees) sampled at a rate of 1:20. In 2012, 400 large R&D-spenders that are included in the survey every year account for 78% of UK business R&D expenditures (ONS, 2012: 14).

The survey questionnaire asks firms to report the number of scientists and technicians (R&D personnel) employed and the R&D expenditures incurred, broken down by location (intramural or extramural), type (basic, applied, experimental, etc.) and source of funding (public or private). The value of public funding from the UK and EU sources are reported separately.[6] All entries for total, privately-funded and publicly-funded R&D correspond to amounts *actually incurred* and/or *received* during the year. This arrangement ties in closely with how *Innovate UK* monitors the subsidized firm's R&D expenditures and pay the subsidy quarterly on the basis of *incurred* expenditures. Therefore, the dataset we have is quite suitable for estimating treatment effects of the subsidy received in a year on the privately-funded R&D expenditures and employment of R&D personnel in that year - even though the firm may have multiple funded projects or each project may be multi-annual.

The characteristics of our sample with respect to privately-funded R&D expenditures, public funding, subsidy intensity and coverage rates are presented in Table 2. Column 1 indicates that privately-funded R&D expenditures are lower than preceding year in 2003 but remains stable from 2008-2010 and records a small increase in 2011 and 2012. On the other hand, private R&D intensity is lower than the preceding year in 2002; and does not recover to the level of

[5] Office for National Statistics (ONS), 2017. See also Anonymous, 2016b.

[6] The privately-funded R&D investment we use in this paper is the difference between total R&D expenditures and the sum of UK and EU subsidies. AS such, privately-funded R&D consists of non-publicly-funded *intramural R&D* and *extramural R&D*. The latter is explicitly defined in the survey questionnaire as privately-funded R&D purchased from or commissioned outside the firm.

2008 in the remaining years from 2009-2012 (column 2). This evidence indicates that firms have tended to reduce their R&D expenditures relative to turnover in response to the bursting of the dot.com bubble in 2002 and during the aftermath of the global financial crisis, particularly from 2009 onwards.

Table 2: R&D expenditures and UK subsidies: By year

(43,650 firms with 201,058 firm/year observations from 1998-2012)

Year	1.Private R&D (£ bn.)	2. Private R&D int. (Private R&D / turnover)	3.Subsidy (£ bn.)	4. Subsidy intensity (Subsidy / Priv. R&D)	5. Coverage (Subsidised firms / total firms)
1998	9.04	0.027	0.91	0.10	0.86
1999	9.53	0.029	0.94	0.10	0.86
2000	9.70	0.028	0.83	0.09	0.77
2001	10.10	0.029	0.69	0.07	0.94
2002	10.50	0.025	0.46	0.04	0.94
2003	7.85	0.034	0.93	0.12	0.97
2004	10.50	0.029	1.17	0.11	0.95
2005	13.00	0.029	1.06	0.08	0.90
2006	14.20	0.024	0.97	0.07	0.92
2007	16.20	0.023	0.95	0.06	0.89
2008	16.50	0.028	0.91	0.06	0.84
2009	16.10	0.022	1.16	0.07	0.97
2010	16.70	0.022	1.17	0.07	0.95
2011	17.60	0.025	1.34	0.08	0.96
2012	17.20	0.023	1.20	0.07	0.97
Average	**12.98**	**0.026**	**0.98**	**0.08**	**0.92**

Note: The sample excludes firm/year observations with R&D intensity is greater than 1. All entries are based on aggregate values for each year and the full period.

In contrast, the level of public funding (column 3) has increased and remained high from 2003-2005 and from 2009-2012. Similarly, the subsidy intensity (the ratio of subsidy to privately-funded R&D expenditures) and the coverage rate (the ratio of subsidized to total number of firms) are relatively higher in 2003-2004 and throughout 2009-2012. This evidence suggests that the funder has been increasing the level of support during crisis periods, perhaps with a view to encourage R&D investment when the firm’s perceived risks and the cost of securing external finance were both higher due the downturn in the business cycle. We test our first hypothesis (H1) to verify whether the funder's increased support after the onset of financial crises has been associated with additionality or crowding-out effects.

Table 3: R&D expenditures and UK subsidies: By age and size deciles
(Pooled panel of 43,650 firms with 201,058 firm/year observations)

Panel A - By age deciles	Private R&D (£ bn.)	Private R&D int. (Private R&D / turnover)	Subsidy (£ bn.)	Subsidy int. (Subsidy / private R&D)	Coverage (Subsidized firms / total firms)
1st decile: age ≤ 3 years	1.27	0.042	0.14	0.11	0.96
2nd decile: 3 < age ≤ 6 yrs.	3.25	0.038	0.14	0.04	0.94
3rd decile: 6 < age ≤ 9 yrs.	6.57	0.034	0.77	0.12	0.93
4th decile: 9 < age ≤ 11 yrs.	8.46	0.046	0.54	0.06	0.93
5th decile: 11 < age ≤ 14 yrs.	14.50	0.041	0.57	0.04	0.93
6th decile: 14 < age ≤ 17 yrs.	15.20	0.033	0.95	0.06	0.92
7th decile: 17 < age ≤ 22 yrs.	29.10	0.033	2.26	0.08	0.92
8th decile: 22 < age ≤ 26 yrs.	26.00	0.023	2.85	0.11	0.90
9th decile: 26 < age ≤ 31 yrs.	31.20	0.024	3.03	0.10	0.91
10th decile: age > 31 years	59.40	0.020	3.43	0.06	0.90
Sample total or (average)	194.95	(0.026)	14.68	(0.08)	(0.92)
Share of top age decile (%)	30.47	n.a.	23.37	n.a.	n.a.
Panel B - By size deciles					
1st decile: 1 employee	0.23	0.015	0.03	0.14	0.96
2nd decile: 2 employees	0.25	0.061	0.03	0.12	0.97
3rd decile: 3 or 4 employees	0.31	0.036	0.04	0.12	0.96
4th decile: 4<employees ≤ 9	0.70	0.028	0.07	0.10	0.95
5th decile: 9<employees≤ 15	0.95	0.017	0.06	0.07	0.94
6th decile: 15<employees≤ 25	1.52	0.029	0.09	0.06	0.94
7th decile: 25<employees≤ 43	2.49	0.023	0.13	0.05	0.93
8th decile: 43<employees≤ 83	4.93	0.020	0.22	0.04	0.92
9th decile: 83<employees≤ 205	11.20	0.024	0.34	0.03	0.91
10th decile: >205 employees	172.00	0.026	13.70	0.08	0.80
Sample total or (average)	194.95	(0.026)	14.68	(0.08)	(0.92)
Share of top size decile (%)	88.23	n.a.	93.32	n.a.	n.a.

Note: Excludes firm/year observations in the top 1% of the private R&D intensity distribution.
n.a.: Not applicable

Table 3 provides further descriptive information by age and size (employment) deciles. It is evident that firms in top-age and top-size deciles account for disproportionately higher proportions of the total subsidy - 23% and 93%, respectively. Secondly, the coverage rate falls slightly with age, but the subsidy intensity does not. Third, both the coverage rate and the subsidy intensity tend to fall with size, the subsidy intensity in the top size decile remains relatively. The fall in subsidy intensity with size is in line with *Innovate UK*'s eligibility criteria summarised in Table 1 above. However, the relative concentration of the subsidy among larger and older firms is evident and may entail high agency costs if the evidence lends support to our second and third hypotheses (**H2** and **H3**) stated above.

Key characteristics of the treated (subsidized) and untreated (non-subsidized) samples and those of the full sample are summarised in Table 4. Rows 2 and 6 indicate that subsidized firms are small R&D spenders and employ a small number of R&D personnel (scientists and technicians) compared to non-subsidized firms. The subsidized firms are also smaller than the non-subsidized firms in terms of turnover and total employment (rows 9 and 10). However, subsidized firms have a relatively higher R&D intensity (rows 3 and 4) and higher R&D personnel intensity (row 7) compared to non-subsidized firms.

Table 4. R&D intensity and firm characteristics by treatment status

	Non-subsidized (Untreated)		Subsidized (Treated)		Whole sample	
	Mean	S.Dev.	Mean	S.Dev.	Mean	S.Dev.
1. Public subsidy (£ 1000)	0	0	79.09	3000.25	73.02	2882.97
2. Privately-funded R&D (£ 1000)	6065.9	45717.4	545.90	15372.05	969.28	19509.76
3. Private R&D to turnover	.058	.146	.089	.150	.087	.150
4. Total R&D to turnover	.058	.147	.101	.178	.098	.176
5. UK subsidy to turnover	0	0	.009	.042	.009	.040
6. R&D personnel employed	34.765	151.847	5.559	83.896	7.835	91.254
7. R&D personnel intensity	0.080	.236	.095	.194	.094	.198
8. Firm age (years)	19.244	10.263	17.087	10.386	17.253	10.392
9. Turnover (£ 1000)	153105	1081527	28371.2	425118.5	37938.2	507617.7
10. Firm employment	70.952	8.125	20.863	5.680	22.897	6.025
11. Start-up dummy (< 3 years old)	.133	.339	.256	.436	.247	.431
12.Young dummy (< 7 years old)	.154	.361	.213	.409	.208	.406
13.Mature (> 14 years old)	.624	.484	.537	.498	.544	.498
14.Old (> 24 years old)	.353	.478	.264	.441	.271	.444
15.Small (<=25 employees)	.338	.473	.565	.496	.547	.498
16. SME (50 to 250 employees)	.259	.438	.225	.418	.228	419
17.Large firm (> 250 employees)	.283	.450	.085	.279	.101	.301
18.Survivor firm (until 2012)	.707	.455	.744	.435	.742	.437
Observations	15421		185637		201058	

Notes: Minimum and maximum values are excluded to comply with non-disclosure requirements of the data host. Excludes observations in the top 1% of the private R&D intensity distribution.

Rows 11 and 12 indicate that start-ups and young firms are relatively more likely to be subsidized as opposed to non-subsidized. In contrast, mature and old firms are less likely to be subsidized as opposed to non-subsidized. We observe a similar pattern with respect to firm size: whilst small firms (25 employees or less) are relatively more likely to be subsidized (row 15), SMEs and large firms (rows 16 and 17) have a relatively lower probability of being subsidized. Finally, survivors (i.e., firms that did not exit during the sample period) have a relatively higher probability of being subsidized.

These descriptive statistics indicate that UK funders (mostly *Innovate UK*) target the subsidy towards firm types that are more likely to create additionality according to **H2** and **H3**. However, the evidence also reflects a preference towards funding firms with a higher level of R&D intensity on average. Also, although older and larger firms have a relatively lower probability of being subsidized, they still account for the major proportion of the total subsidy – mainly due to high coverage rates and size effects presented in Tables 2 and 3 above.

Methodology

Our aim is to estimate the average treatment effect on the treated (ATT) for privately-funded R&D intensity - and for the share of R&D personnel in total employment as a sensitivity check. The ATT is estimated by comparing the firm's privately-funded R&D intensity (and share of R&D personnel) when it receives the subsidy with the same firm's counterfactual outcome that would have been observed had it not received the subsidy. The counterfactuals are selected based on matching difference-in-difference estimations, which help to reduce biases that arise in the context of observational data (Heckman et al., 1998; Smith and Todd, 2005).

$$ATT_t = E(Y_{i,t}^1 \mid \mathbf{X}_{t-1}, S_{i,t}=1) - E(Y_{i,t}^0 \mid \mathbf{X}_{t-1}, S_{it}=1) \qquad (1)$$

Here, $t = 1, 2 \ldots \tau$ is the time dimension over which the data is pooled (when $t > 1$) or a single cross-section when $t = 1$; and $i = 1, 2 \ldots N$ is the number of firms in the sample. $Y_{i,t}^1$ is the outcome (privately-funded R&D intensity) of the treated firm; $Y_{i,t}^0$ is the counterfactual outcome of the same firm had it been untreated; $S_{i,t}$ is the treatment status, which is 1 when the firm receives subsidy and 0 otherwise; $\mathbf{X}_{t-1}$ is the set of pre-treatment (lagged) covariates that determine selection into treatment; and E is the expectation operator.

It is obvious that the two outcomes are not observable at the same time. To ensure identification, we draw on the exchangeability condition which is satisfied if: (i) the treatment is un-confounded when selection into treatment is conditioned on pre-treatment covariates $\mathbf{X}_{t-1}$; and (ii) there is sufficient overlap (or common support) between treated and control groups given the conditioning covariates in $\mathbf{X}_{t-1}$ (Rosenbaum and Rubin, 1983).

Conditioning on all relevant covariates may be difficult if the covariates vector, $\mathbf{X}_{t-1}$, is multidimensional. To address this problem, Rosenbaum and Rubin (1983) suggest using the so-called balancing scores, which are a function of $\mathbf{X}_{t-1}$. One such balancing score is the propensity score – i.e., the probability of selection into treatment given the observed covariates in $\mathbf{X}_{t-1}$. The propensity score would also ensure conditional independence if the potential outcomes are independent of treatment conditional on covariates in $\mathbf{X}_{t-1}$. Denoting the estimated propensity score as $\widehat{p_\iota}(\mathbf{X_{t-1}}) = \widehat{p_\iota}(S_{i,t} = 1 \,|\, \mathbf{X_{i,t-1}})$, the estimated ATT can be written as follows:

$$\widehat{ATT_t} = \left(N^{-1} \sum_{i=1}^{N} S_{i,t}\right)^{-1} \left\{\sum_{i=1}^{N} \frac{[S_{i,t} - \widehat{p_\iota}(\mathbf{X}_{i,t-1})Y_{i,t}}{1 - \widehat{p_\iota}(\mathbf{X}_{i,t-1})}\right\} \quad (2)$$

The ATT estimator in (2) is shown to have the smallest asymptotic variance if the conditional independence assumption (CIA) is satisfied (Wooldridge, 2010). Also, Hirano et al. (2000) have demonstrated that it achieves the semiparametric efficiency bound obtained by Hahn (1998). Essentially, the ATT is the average of the difference between the potential outcomes for the treated and counterfactual (control) groups in the treated subsample; and the first term in (2), $\left(N^{-1} \sum_{i=1}^{N} S_{i,t}\right)^{-1}$, is an unbiased estimator of the probability of treatment, i.e., $P(S_{i,t} = 1)$.[7] The estimations are based on propensity score matching with pooled data (when $\tau > 1$) and with cross-section data for each year (when $\tau = 1$).

We estimate the propensity scores with a probit estimator. Following Rosenbaum and Rubin (1983), we use a flexible probit model, where X and various functions of X (e.g., quadratics and interactions) are included. The probit model is stated below.

$$\mathrm{P}(S_t = 1 |\, \mathbf{X}_{t-1}) = \boldsymbol{\Phi}(\mathbf{X}_{t-1}\boldsymbol{\beta}) \quad (3)$$

[7] Although we report only ATTs in the paper, we have estimated ATEs too. The two are very close, with any difference usually observed in the third digit after the decimal point.

Here P($S_t = 1| X_{t-1}$) is probability of selection into treatment (receiving the R&D subsidy) conditional on the vector of one year lagged firm characteristics $\mathbf{X}_{t-1}$, Φ is the standard normal distribution function, $\boldsymbol{\beta}$ is a vector of parameters to be estimated; and $\mathbf{X}_{t-1}$ is a vector of firm characteristics that impact on selection into treatment and outcome, as listed in Table A1 in the Appendix.

The matching procedure is based on the statistical package of Leuven and Sianesi (2018); and carried out with both 1 and 10 nearest neighbours. The one-neighbour matching provides lower estimator bias but higher variance compared to the ten-neighbour matching (Caliedo and Kopeinig, 2008). The ATT is obtained by bootstrapping over 1,000 replications.

Following Rubin (2001), Imbens and Rubin (2015) and Sianesi (2004), we conduct a range of diagnostic tests to verify the matching quality, which is necessary for satisfying the exchangeability condition. These include: (i) propensity score tests for mean equality of the covariates for treated and untreated firms; (ii) measures of mean and median standardised biases between the treatment and comparison groups; (iii) the extent of common support necessary to satisfy the overlapping condition; (iv) the pseudo R-squared after matching; and (v) the performance of the probit model in terms of correct classification and the area under the receiver operating characteristic (ROC) curve. We conduct these diagnostics for all results based on different firm cohorts, different time periods and annual cross-sections.

In addition to matching quality checks, we also compare the ATTs from the PSM estimator with those based on a doubly-robust (DR) estimator that provides some assurance against misspecification of the selection (propensity score) or outcome model (Emsley et al., 2008; Funk et al., 2011). Both PSM and DR require absence of unmeasured confounders, but they allow for causal inference similar to quasi randomized control trials. The advantage of the DR estimator is that it provides unbiased estimations if either the selection or outcome model is correctly specified. Simulations indicate that the DR estimator: (a) provides efficiency gains over inverse probability of treatment-weighted (IPTW) estimators (Emsley et al., 2008); and (b) is unbiased when a covariate is omitted from one (but not both) of the constituent models (Funk et al., 2011). However, the DR estimator may be less efficient than the PSM (Emsley et al., 2008).

The algorithm for the DR estimator can be stated as follows (Emsley et al., 2008):

1. Estimate the selection model using the covariates that determine selection into treatment (subsidy); and obtain the estimated propensity scores;
2. Predict the value of the outcome (privately-funded R&D intensity) in the treated group, given the covariates in the outcome model
3. Predict the value of the outcome in the untreated group, given the covariates in the outcome model
4. Find the difference between (2) and (3)
5. To obtain the ATT, regress the difference in (4) on a constant and over the treated sample (i.e, when $S_{i,t} = 1$), with bootstrapping.

The covariates in the selection model of the DR estimator are the same as those used in the PSM estimations. On the other hand, the outcome model include the covariates in the selection model and three additional covariates that feature in R&D investment moels. These consist of the logarithm of firm age, the Herfindahl index of market concentration, and the square of the latter. The logarithm of age is included because it has been often reported as a determinant of R&D investment, with the latter declining with age (Huergo and Jaumandreu, 2004; Balasubramanian and Lee, 2008). Market concentration at 3-digit industry level and its square are included in line with Schumpeterian models of competition and innovation that report an inverted-U relationship between competition and R&D investment (Aghion et al, 2005; Polder and Veldhuizen, 2012).

As a further robustness check, we estimate the ATT for the effect of subsidy on the ratio of R&D personnel (scientists and technicians) to total employment. This is warranted for two reasons. First, the employment of R&D personnel is an important input measure of innovation and the extent of additionality in this input has both policy and welfare implications. Secondly, and more to the point here, it is important to verify if the treatment effects on the intensity of R&D personnel are similar to those related to R&D intensity; and whether the evidence on the former also tallies with our hypotheses stated above.

The checks above notwithstanding, we are aware that the use of pooled panel data may pose some challenges for treatment-effect estimations. First, firms may be in receipt of subsidy for several times over the analysis period when the data is pooled. Therefore, it may be difficult to disentangle the effect of subsidy in a particular year from the effect of subsidies in previous years. We address this issue by lagging the treatment (subsidy) indicator one and two years to verify if the effect-size estimate differs with lagged treatment. Secondly, the firm may receive subsidy from more than one funder over the estimation period – for example form UK and EU funders as it is the case in our data. To address this issue, we regress the stored treatment effects on a dummy variable that takes the value of one if the firm receives both UK and EU subsidies; and zero otherwise.[8] The third issue is potential time-series dependence that is ignored in the calculation of the standard errors in most empirical work in the field. To address this issue, we use panel bootstrapping that resamples all time periods for each firm in the pooled data (Wooldridge, 2010).

5. Results

Summary statistics for the covariates in the selection model are presented in Table A1 in the Appendix, whereas probit results for pooled data and selected cross-sections are presented in Table A2. The probit results indicate that firms with multi-plant units are more likely to receive the subsidy. Also, there is evidence of non-linear relationship between the probability of receiving the subsidy and firm size in terms of employment and turnover. The findings are usually similar for the whole period (1998-2012), selected years and firm types in terms of age and size. Given that the PSM estimator requires correct specification of the selection model, we ensure that the probit results satisfy four requirements: (i) it includes covariates that reflect the size-dependent criteria that *Innovate UK* utilizes for determining eligibility (Table 1); (ii) the rate of correct correctly classifying the subsidy status is satisfactory; (iii) the area under the receiver operating characteristic (ROC) curve is large enough; and (iv) the model is conducive to satisfactory matching-quality diagnostics as suggested by Rubin (2001), Imbens and Rubin (2015), and Sianesi (2004).

The selection model satisfies the first criterion in that it control for firm size and its square. The post-estimation statistics for the probit results (last 3 rows in Table A2 in the Appendix) also satisfy the second and third criteria because: (a) the area under the ROC curve is mostly over 70%, a threshold considered satisfactory in observational data (Hosmer *et al.*, 2013); and (b)

[8] We find that the average treatment effect is smaller when the treatment dummy is lagged one year or two years. However, the average treatment effect is larger if the firm receives both EU and UK subsidies. The results are not reported here but they can be provided on request.

the rate of correct classification is over 90%. These statistics indicate that the model is satisfactory in distinguishing between the treated and untreated firms; and it correctly identifies more than 90% of the firms receiving subsidy.

ATTs for privately-funded R&D intensity with bootstrapped standard errors are presented in Tables 5 and 6. [9] Whilst Table 5 reports the results for the whole sample, two sub-periods and for cross sections in each year; Table 6 reports the results by firm age and size over the whole period.

The matching quality statistics in Tables 5 and 6 are highly satisfactory and well within the ranges suggested by Rubin (2001) and Imbens and Rubin (2015). The mean and median bias are less than 5% for almost all periods (except 2007 where the mean bias is 5% but the median bias is 3%). Secondly, the absolute standardized differences of the means for treated and control groups is less than the conventional level of 25%. Also, after matching, the pseudo R-squared is close to zero and indicates that the matching covariates have little joint explanatory power in explaining the selection in the matched samples. This statistic lends support to the orthogonality condition of the treatment, conditional on the propensity scores (Sianesi, 2004). Finally, both the results in the last column of Tables 5 and 6 and the graphical diagnostics in Figure A1 in the Appendix indicate good common support and satisfactory balancing of the covariates after matching.

Having verified the predictive power of the selection model and the quality of matching, we can now verify the consistency of the ATT estimates between the DR and PSM estimators.[10] Out of 28 result pairs, 90% reflect sign and significance consistency between PSM and DR estimations. The difference between the ATT pairs is observed in 2004, 2010 and 2011, where the DR estimator indicates crowding-out effects, but the PSM estimator indicates no effect for 2004 and 2010, and a small additionality effect for 2011. The results across two estimators are also quite similar in terms of magnitude. The magnitude of the treatment effect is similar in

[9] We carry out panel bootstrapping when the data is pooled and normal bootstrapping for cross-sections, all with 1,000 replications.

[10] The average treatment effects in the population (ATEs) is similar to the ATTs reported here, with difference between the two mostly observed in the third digit after the decimal point. ATEs are not reported here, but they are available on request.

82% of the result pairs, with the exception of the second sub-period (2008-2012) and years 2004, 2006, 2009 and 2010[11].

Table 5: ATTs for UK subsidy and private R&D intensity

(DR and one-neighbour PSM estimators, by periods and years}

Period/Year	Double Robust	PSM	Mean Bias (%)	Median Bias (%)	Balance (%)	Pseudo R^2	Observations on common support
1998-2012	.0304*** (.0015)	.0289*** (.0011)	0.3	0.2	3.0	0.000	Untreated: 14,989 Treated: 179,533
1998-2007	.0434*** (.0016)	.0404*** (.0018)	1.3	0.7	5.6	0.000	Untreated: 9,731 Treated: 94,285
2008-2012	.0102*** (.0024)	.0169*** (.0024)	0.5	0.7	5.0	0.000	Untreated: 5,258 Treated: 85,214
1998	.0392*** (.0045)	.0434*** (.0048)	2.7	2.5	9.8	0.002	Untreated: 1,062 Treated: 6,636
1999	.0520*** (.0048)	.0525*** (.0060)	0.6	0.6	12.3	0.003	Untreated: 946 Treated: 5,990
2000	.0620*** (.0031)	.0608*** (.0040)	0.7	0.6	7.6	0.001	Untreated: 1,752 Treated: 5,991
2001	.0376*** (.0086)	.0392*** (.0096)	0.4	0.2	8.0	0.001	Untreated: 417 Treated: 6,951
2002	.0140*** (.0011)	.0265*** (.0086)	0.9	0.5	8.7	0.002	Untreated: 556 Treated: 9,096
2003	-.0588*** (.0221)	-.0663*** (.0229)	1.9	2.5	20.4	0.007	Untreated: 240 Treated: 7,603
2004	-.0194* (.0150)	-.0068 (.0128)	1.4	1.0	7.0	0.001	Untreated: 371 Treated: 9,380
2005	.0538*** (.0047)	.0518*** (.0040)	2.1	0.8	11.9	0.003	Untreated: 1,144 Treated: 10,719
2006	.0116*** (.0047)	.0199*** (.0037)	4.4	2.6	17.0	0.005	Untreated: 1,216 Treated: 14,657
2007	.0220*** (.0042)	.0243*** (.0032)	5.0	3.0	18.1	0.006	Untreated: 2,021 Treated: 16,776
2008	.0429*** (.0032)	.0485*** (.0037)	1.6	1.4	9.9	0.002	Untreated: 2,598 Treated: 12,990
2009	-.0656*** (.0013)	-.0472*** (.0104)	2.2	1.6	13.4	0.003	Untreated: 522 Treated: 17,285
2010	-.0216*** (.0091)	.0108 (.0071)	0.3	0.3	3.3	0.000	Untreated: 799 Treated: 16,269
2011	-.0055** (.0053)	.0159** (.0072)	1.0	0.8	3.7	0.002	Untreated: 786 Treated: 18,203
2012	-.0458*** (.0046)	-.0403*** (.0105)	1.1	1.0	11.6	0.002	Untreated: 552 Treated: 20,069

Notes: PSM is based on 1-neighbour matching. Mean Bias, Median Bias, Pseudo R^2 and Balance are post-matching diagnostics. Conventionally, the balance should be less than 25% (Rubin, 2001). All covariates for matching are the same (see Table A1) and lagged one year. The outcome variable is ln(Private R&D intensity + 1), where private R&D intensity, the ratio of R&D expenditures to firm turnover, ranges between 0 and 1. Standard errors (in brackets) are based on bootstrapping with 1000 iterations of random sampling.
*, **, *** indicate significance at 10%, 5% and 1% respectively.

[11] This pattern of consistency (and occasional divergence) is also observed in tables A3 and A4 in the Appendix, where the PSM is based on ten-nearest-neighbour matching.

The evidence in both tables confirms that the treatment effect is heterogeneous and this is in line with the literature reviewed above. The ATT over the full period (1998-2012) is positive but small (0.0263). It indicates that the average R&D intensity of the treated firms would have been 2.63% lower had there been no public support.[12] The ATT is smaller in the second period (2008-2012) and varies between years (Table 5) and between firm types (Table 6). Across two tables, 30 results (53.5%) indicate additionality effects, 22 results (39.4%) indicate crowding-out effects and 4 results (7.1%) indicate no effect. In Table 5, the statistically-significant additionality effect ranges between 1.2% and 6.2%, and the crowding-out effect varies from -0.6% to -6.6%. Similarly we observe heterogeneity in the statistically-significant ATTs in Table 6 too, where the additionality effect ranges from 1.7% to 7%, and substitution effects from -2% to -5.8%.

A highly similar pattern emerges in Tables A3 and A4 in the Appendix, where matching is conducted with 10 nearest neighbours. Furthermore, the pattern is almost the same in Tables A5 and A6 in the Appendix, where we report ATTs for the effect of the public support on the ratio of R&D personnel (scientists and technicians) to total firm employment.

Given this variation, we recommend that future research adopt a systematic approach aimed at discovering the sources of heterogeneity in the treatment effects – particularly, when the latter is about the effect of public support on innovation inputs (business R&D investment or employment of R&D personnel). Otherwise, ATT estimates based on aggregate samples covering different periods or different firm types are likely to conceal a high degree of heterogeneity and as such would constitute a poor basis for evidence-based public policy.

Having noted that, we can now proceed to verify if the findings lend support to our hypotheses about the sources of heterogeneity in the ATTs. Our findings in Table 5 concerning privately-funded R&D intensity lend reasonable support to the first hypothesis (**H1**), which posits that the ATTs would be smaller or indicate crowding-out effects after the onset of financial crises. Indeed, the ATTs are smaller or negative: (i) after the bursting of the *dot.com* bubble from 2003-2004; and (ii) after the onset of the global financial crisis from 2009-2012.[13] During these

[12] Note from Table 4 that the privately-funded R&D intensity in the treated sample is 0.089. Had there been no treatment, the privately-funded R&D intensity would have been 0.0865.
[13] The trough for the *dot-com* bubble crisis is 2002 (Lowenstein, 2004); and for the global financial crisis it is 2009 (Bartram and Bodnar, 2009).

post-crisis periods, firms tended to substitute public subsidy for privately-funded R&D as their incentive constraints have tightened due to risk aversion under incomplete contracting. Crowding-out or insignificant effects after the financial crises are also observed in Table A5 in the Appendix, where we report the treatment effects on the employment of R&D personnel (scientists and technicians).

We relate these results to risk-aversion under incomplete contracting. On the one hand, risk-averse firms would either reduce R&D investment or seek added insurance as the onset of the crisis leads lower expected growth and higher costs of external finance for R&D investment (Acemoglu and Linn, 2005; Bloom, 2007; and Dubois et al., 2015). On the other hand, the absence of an enforcement mechanism in the subsidy contract and increased noise in R&D investment as an indicator effort would reduce the ability of the funder to ensure R&D additionality. Under these conditions, the actual allocations of the subsidy and R&D investment deviate from the first-best allocations and increases the probability of observing substitution effects or no effects on privately-funded R&D investment.

In the data, we observe substitution effects or absence of additionality effects approximately one year after the trough of the two crises. This is in line with Hud and Hussinger (2015), who report crowding-out effects from German data in 2009. However, our findings contribute to existing knowledge about the relationship between financial crises and effect-size heterogeneity in two ways. First, we demonstrate that substitution effects or absence of additionality effects are not limited to the recent crisis only. Secondly, we demonstrate that such second-best outcomes are underpinned by risk aversion and incomplete contracting. Therefore, similar outcomes are likely to be observed during future crisis episodes too. With respect to the UK context, our findings indicate that UK funders (mostly *Innovate UK* and its predecessor) have moved to satisfy the incentive constraints of the risk-averse firms by increasing the level of subsidy, its intensity and the coverage rate after the onset of the crisis. However, the move does not appear to have induced the desired additionality effects. According to contract theory, this is due to a combination of two factors: either the increased subsidy did not provide sufficient insurance for the risk-averse firms or the latter have extracted agency rents due to incomplete contracting.

Turning to Table 6, we observe that the ATTs vary with firm age and size. The results indicate higher additionality effects among younger and smaller firms, but crowding-out effects among older and larger firms. The same pattern is observed in table A6 in the Appendix, where we report the effects of the subsidy on the employment of R&D personnel by firm type. In both sets of results, the ATTs decline with age and size and eventually indicates higher substitution effects as age and size increases[14]. These findings lend strong support to our second and third hypotheses (**H2** and **H3**), which posits that older and larger firms are more likely to benefit from concealing their true types in terms of R&D efficiency.

Table 6: ATTs for UK subsidy and private R&D intensity

(DR and one-neighbour PSM estimators, by firm age and size types)

Outcome variable: log(private R&D intensity + 1)

Firm type	**Double Robust**	**PSM**	**Mean Bias (%)**	**Median Bias (%)**	**Balance (%)**	**Pseudo R^2**	**Observations on common support**
Firm type by age							
Start-ups from 1998 to 2007	.0694*** (.0006)	.0701*** (.0053)	0.9	0.7	13.0	0.003	Untreated: 851 Treated: 14,398
Start-ups from 2008 to 2012	.0165*** (.0004)	.0278*** (.0072)	2.8	2.5	19.2	0.007	Untreated: 1,046 Treated: 28,575
Young1: <= 7 years	.0361*** (.0003)	.0413*** (.0048)	2.1	1.8	14.5	0.004	Untreated: 1,898 Treated: 42,995
Young2: > 7 and < =14 years	.0193*** (.0002)	.0205*** (.0012)	0.4	0.4	3.4	0.000	Untreated: 12,820 Treated: 144,854
Mature: >14 years	-.0570*** (.0003)	-.0559*** (.0036)	1.5	1.5	9.3	0.002	Untreated: 3,402 Treated: 12,571
Old: > 24 years	-.0492*** (.0003)	-.0495*** (.0038)	1.4	1.4	9.7	0.002	Untreated: 2,291 Treated: 8,405
Firm type by size							
Small: > 10 and < 50 employees	.0271*** (.0001)	.0276*** (.0017)	0.8	0.5	2.9	0.000	Untreated: 4,110 Treated: 57,545
SMEs: >=50 and <=250 employees	-.0199*** (.0002)	-.0221*** (.0024)	1.0	1.0	3.4	0.000	Untreated: 3,909 Treated: 41,293
Firms in the upper quartile: >=60 employees	-.0352*** (.0002)	-.0338*** (.0024)	0.6	0.5	6.2	0.001	Untreated: 7,678 Treated: 50,885
Large: > 250 employees	-.0559*** (.0002)	-.0581*** (.0034)	1.7	1.6	9.4	0.004	Untreated: 4,266 Treated: 15,480

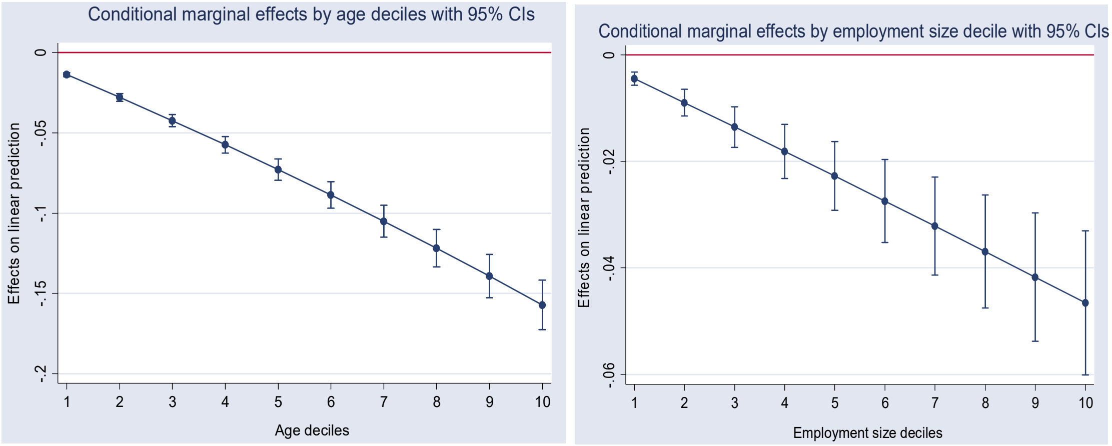
Notes: See Table 5.

Results in Table 6 indicate that the decay in the estimated ATTs becomes observable at surprisingly younger ages and smaller sizes. Indeed, subsidies start to be associated with crowding-out effects when the firm age is over 14 years and the firm size is 50 employees or more. To verify whether these results may be reflecting a potential bias due to pooled data, we regressed the stored treatment effects on age and size deciles over the full period and for cross-sections in every year. Some of results are presented in Figure 1, where we plot the conditional

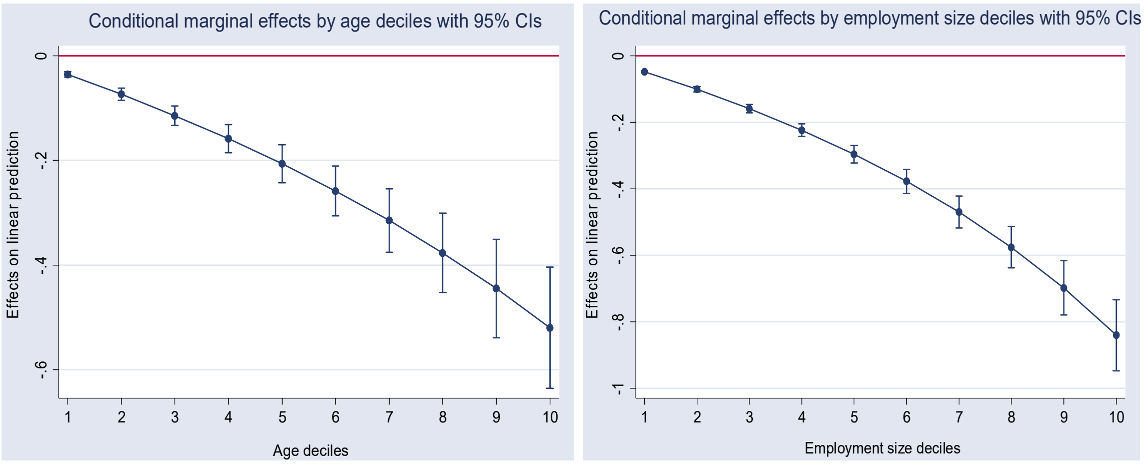
[14] Note that the additionality effects among start-ups are lower during the second sub-period (2008-2012), which covers the extended recession after the global financial crisis.

elasticities of the treatment effect with respect to age and size deciles for the full period (Panel A) followed by those for a typical year 2000 (Panel B).

Figure 1: Conditional elasticities of the ATTs with respect to age and size deciles[15]



Panel A: Pooled data from 1998-2012



Panel B: Cross-section data for year 2000 only

The results indicate that the decay's pattern is strikingly similar between pooled data and the annual cross sections. The wider range for the elasticities in year 2000 compared to the full

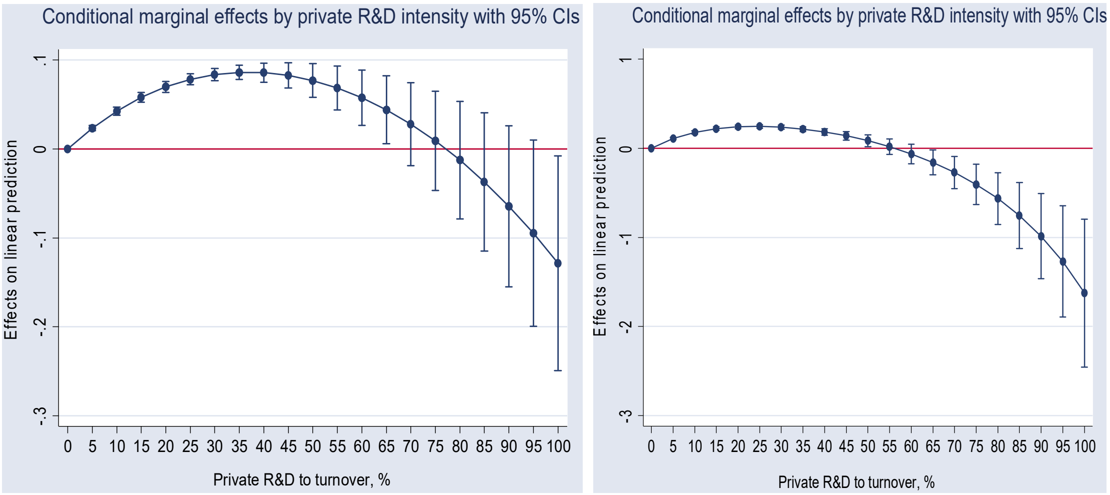
[15] The graphs in Figure 1 are based on the following regression: $TT_{ij} = ATT_0 + \mathbf{D}\boldsymbol{\gamma} + \varepsilon_{ij}$, where TT is the stored value of each matched outcome in the treated sample; ATT_0 is the average treatment effect when all age or size deciles are zero; i is firm; j is age or size decile from 1 to 10; **D** is a vector of cut-off points for age or size deciles; $\boldsymbol{\gamma}$ is vector of parameters on age and size decile cut-off values; and ε is the error term. We used *Stata*'s margins command to obtain the conditional marginal effects of age and size on ATTs as elasticities. Results for other years have similar trends. Also, the results are similar for treatment effects on employment intensity of R&D personnel. The latter are not reported here to avoid overcrowding, but both sets are available on request.

period is to be expected because the ATT in 2000 is 0.0608 compared to the ATT of 0.0263 in the full sample. Note that a negative elasticity does not indicate crowding-out, but it does indicate that the ATT would get smaller as age or size increases. We see that the crowding-out effect becomes observable after the second age and size deciles in the pooled data and in the cross-section for 2000, where the magnitude of the negative elasticity begins to be larger than the ATT in the relevant sample. Therefore, we conclude that the age- and size-dependent decline in the ATTs reported in Table 6 is not likely to be biased due to time dependence in the pooled data.

Finally, we investigate whether our fourth hypothesis is supported by the data. **H4** posits that the treatment effect will follow an inverted-U pattern when evaluated against the distribution of the R&D intensity in the sample. To verify this relationship, we regressed the stored ATTs from the pooled data and from the yearly cross-sections on R&D intensity and its square. The results, expressed as conditional elasticities of ATTs with respect to R&D intensity, are presented in Figure 2.

Figure 2: Conditional elasticities of the ATTs

with respect to privately-funded R&D intensity percentiles[16]



Pooled data for 1998-2012 ***Based on data for 2000***

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[16] The graphs in Figure 2 are based on the following regression: $TT_{ij} = ATT_0 + \mathbf{RD}\boldsymbol{\mu} + v_{ij}$. Here **RD** is the cut-off values for the privately-funded R&D intensity percentiles and $\boldsymbol{\mu}$ is the set of parameters. Other terms and the derivation of the conditional elasticities are as explained in note 15 above. The results are similar when the stored treatment effects are regressed on total R&D intensity; and for treatment effects on employment intensity of R&D personnel. The latter are not reported here to avoid overcrowding, but bot sets are available on request.

It can be observed that the ATTs are larger than the average as the R&D intensity increases until about the 35th percentile of the R&D intensity in both pooled and cross-section data. Thereafter, the elasticity of the treatment effect with respect to R&D intensity declines and becomes negative after the 75th percentile in the full sample and the 60th percentile in 2000. Because the confidence intervals are wide in the pooled sample, we can infer a crowding-out effect at 10% significance from the 85th percentile onwards. However, we can infer a crowding –out effect from the 65th percentile onward in the cross section for 2000.[17] These results lend support to hypothesis **H4**, which posits that the ATT would follow an inverted-U pattern when evaluated against the distribution of the R&D intensity.

The quadratic relationship between ATTs and R&D intensity is driven by the changing balance between the complementarities of the research effort and research productivity to R&D investment. As indicated earlier, the subsidy is more (less) likely to be associated with additionality effects when the complementarity of the firm's research effort with R&D investment is larger (smaller) than the complementarity of research productivity with R&D investment. As the complementarity of the research productivity dominates at higher levels of R&D intensity, the firm can extract additional informational rents by pretending to be a low-productivity type, and this leads to either crowding-out or smaller additionality effects. Given that the R&D intensity of the subsidized firms is approximately 50% higher than the R&D intensity of the non-subsidized firms in the data (Table 4), the UK funder's targeting of relatively more R&D-intensive firms is in line with the predictions of the contract theory. The latter expects the principal to use the observed R&D as a proxy for unobserved research effort and productivity. However, reliance on proxy performance indicators does not resolve the agency problem that, in this case, emerges as a tendency of the more efficient firms mimicking the low-efficiency firms and thereby extracting informational rents.

Conclusions

We have investigated the effects of UK subsidies on privately-funded R&D intensity and employment of R&D personnel using a sample of 43,650 R&D-active UK firms from 1998 to

[17] This is because the magnitude of the negative elasticity is larger than the ATT in after these deciles in both samples, with the implication that the ATT falls by more than the average in the sample when R&D intensity increases by one percent.

2012. The results are obtained from double-robust and matching difference-in-difference estimators with different degrees of control for self-selection and heterogeneity. The matching quality across almost all covariates and sub-samples are satisfactory, and the estimated results are highly consistent across estimators and innovation inputs.

Our findings are in line with insights from the contract theory, which predicts that public support for R&D would be conducive to second-best allocations of the subsidy and of the R&D effort in the presence of risk aversion and asymmetric information about the firms' true types. We find that the ATT is smaller or indicates crowding-out effects among older and larger firms, which have relatively higher levels of efficiency in converting the R&D investment into quality innovations/products. We also find that, in the absence of a third-party enforcer of the contract, risk aversion and non-verifiability of the effort due to noisy proxies for performance combine to generate substitution or insignificant effects roughly one year after the onset of financial crises. Finally, we find that the treatment effect follows an inverted-U pattern when evaluated against R&D intensity. The latter finding is also explained by the theory of contracts, which predicts substitution effects or smaller additionality effects when the complementarity of the firm's research productivity (i.e., its efficiency in converting the R&D inputs into quality products/innovations) with R&D investment dominates the complementarity of its research effort with R&D investment. Our findings are highly consistent across two estimators (DR and PSM) and two innovation inputs (privately-funded R&D intensity and intensity of R&D personnel employment).

One implication of our analysis for future empirical work is that treatment effects based on pooled samples or cross-sections of heterogeneous firm types may conceal a high degree of heterogeneity; and as such, they provide a poor basis for evidence-based public policy. Another implication is that firm-level panel data with repeated treatments poses some challenges for empirical work, but also provides opportunities for tracing the level of heterogeneity in the treatment effects and for identifying the observable sources thereof. The third implication can be stated as follows: given the extent of heterogeneity in the treatment effects, future research should pay more attention to the theoretical underpinnings of effect-size heterogeneity. In this article, we have drawn on the theory of contracts to demonstrate that the principal-agent problems that arise under information asymmetries and contract incompleteness go a long way in explaining effect-size heterogeneity. We encourage further testing of the insights from contract theory and further modelling of alternative mechanism designs.

A key policy implication of our findings is that public support for R&D investment cannot deliver first-best outcomes (induce optimal R&D investment) when firm research efforts and research productivity types are unobservable and represent private knowledge of the firm. The observed level of R&D investment is an imperfect/noisy indicator of true innovation performance or a true firm type, hence public subsidization and monitoring of business R&D investment are highly likely to produce second-best outcomes that involve either sub-optimal additionality effects or substitution effects. We show in this paper that these effects depend on firm age, size, R&D intensity, and business cycle conditions. In addition to supporting cash-constrained small and young companies, public support for R&D should rely more on *ex post* rewards for realised innovations that satisfy social-welfare criteria as demonstrated by Akcigit et al. (2017) in the context of the US R&D tax credits system, instead of schemes solely aimed at reducing the cost of R&D investment *ex ante*.

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APPENDIX

Table A1: Summary statistics for covariates in the selection model*

	Firms without R&D subsidy		Firms with R&D subsidy		All	
	Mean	SD	Mean	SD	Mean	SD
Outcome	.049	.113	.077	.117	.075	.117
UK subsidy dummy	.049	.113	.077	.117	.075	.117
Log (employment)	4.262	2.095	3.038	1.737	3.131	1.796
Log (employment squared)	22.557	19.617	12.248	12.617	13.039	13.565
Log (number of local units)	2.250	4.808	1.087	4.020	1.243	4.149
Log(deflated turnover)	8.708	2.727	7.190	2.394	7.307	2.455
Log(deflated turnover) squared	83.277	48.504	57.439	35.706	59.422	37.482
Log(deflated turnover)* Log(employment)	42.202	30.584	25.659	21.212	26.928	22.507
Log (employment)*(numb. of local units)	87.68	1418.54	21.687	601.531	26.749	699.089
Number of local units	9.492	122.426	2.964	55.711	3.465	63.389
Observations	15421		185637		201058	

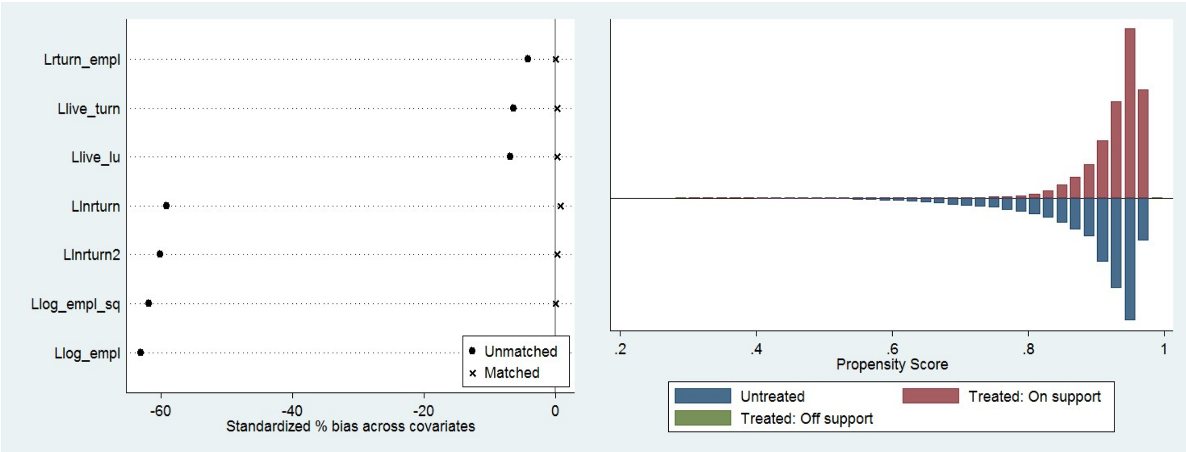
* Minimum and maximum values are not reported to comply with non-disclosure requirements of the data host, UK Data Service. Firm/year observations with privately-funded R&D intensity larger than one are excluded. The estimation period is from 1998 to 2012. All covariates are lagged one year in the estimations.

Table A2: Selected probit estimation results and post-estimation diagnostics

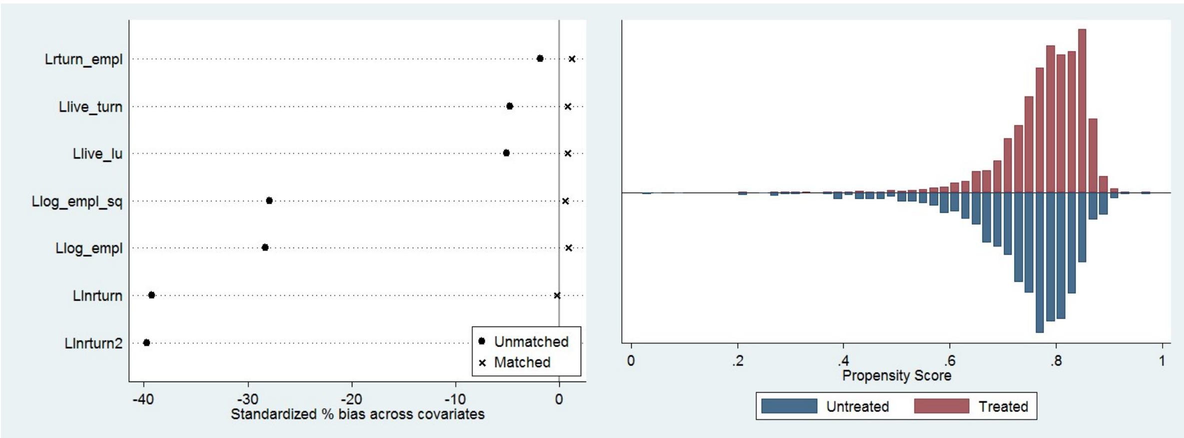
	Full sample	Year 2001	Year 2009	Year 2012	Mature firms	Large firms
Log (employment)	.021	0.055	0.194*	0.197**	0.149***	-1.203***
Log (employment squared)	-.018***	-0.014*	-0.051**	0.005	-0.030***	0.068***
Log (number of local units)	.024***	0.029**	0.006**	0.018***	0.058***	0.004***
Log(deflated turnover)	.118**	0.221***	0.030**	0.048	0.094*	0.449***
Log(deflated turnover) squared	-.012***	-0.020***	-0.010**	-0.003	-0.012***	-0.021***
Log(deflated turnover)* Log(employment)	.00003***	0.000	0.081***	-0.034*	0.000	0.000
Log (employment)*(numb. of local units)	-.0015***	-0.0018**	-0.0004**	-0.0002*	-0.004***	-0.0002**
Observations	201058	7494	17814	20681	157680	19752
Area under ROC curve (%)	70.94	75.4	78.49	72.28	69.6	70.43
Correct classification (%)	92.24	94.62	97.06	97.30	91.95	88.44
Positive predictive value	92.36	94.35	97.11	97.37	91.82	88.68

Note: *, **, *** indicate significance at 10%, 5%, and 1% respectively. All covariates are lagged one year.

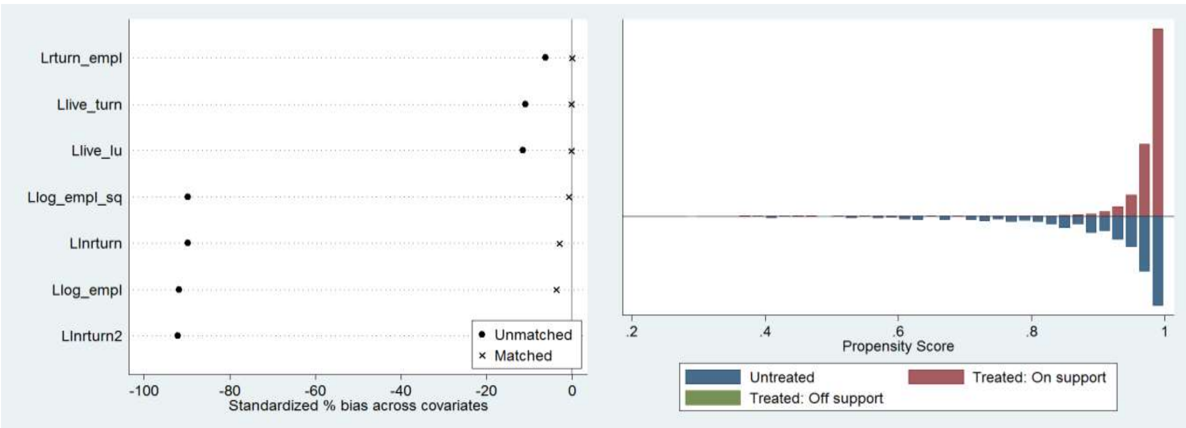
Figure A1: Matching diagnostics for selected samples



1: Full sample from 1998-2012

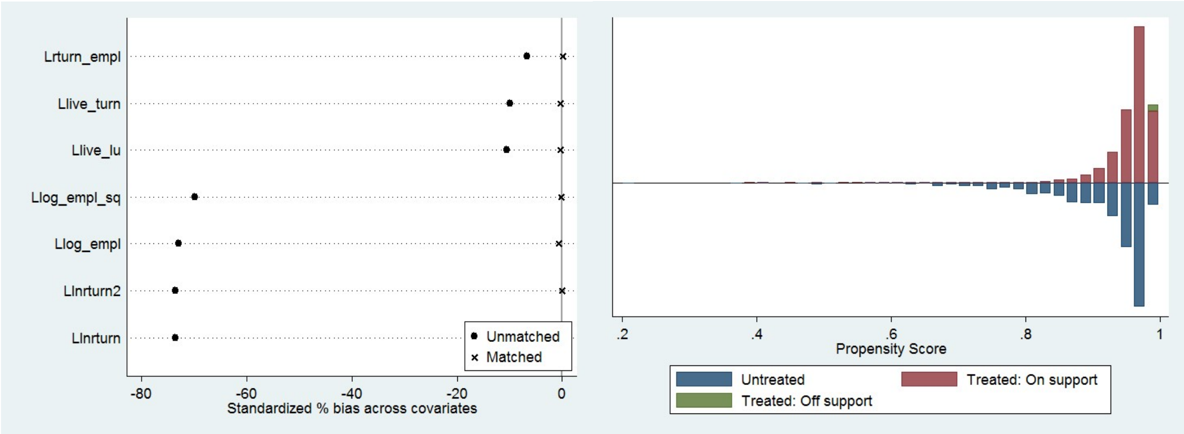


2: Year 2000

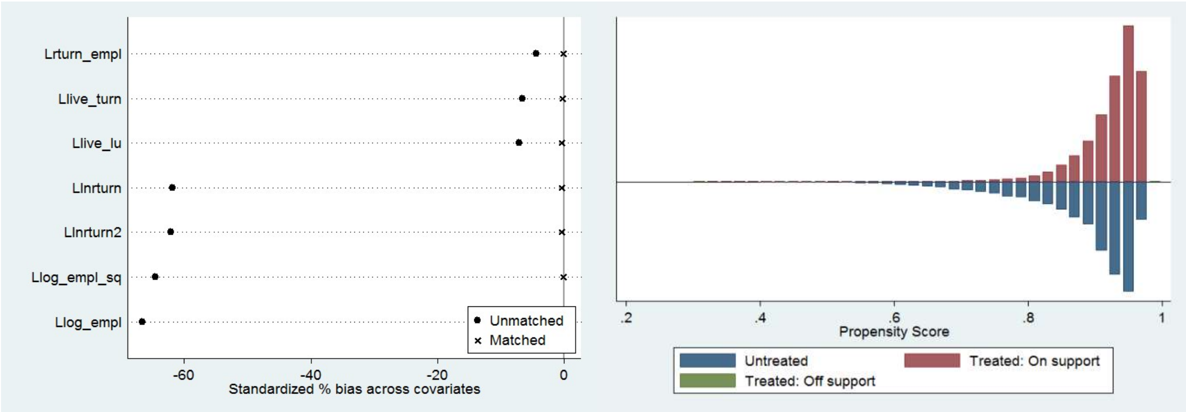


3: Year 2009

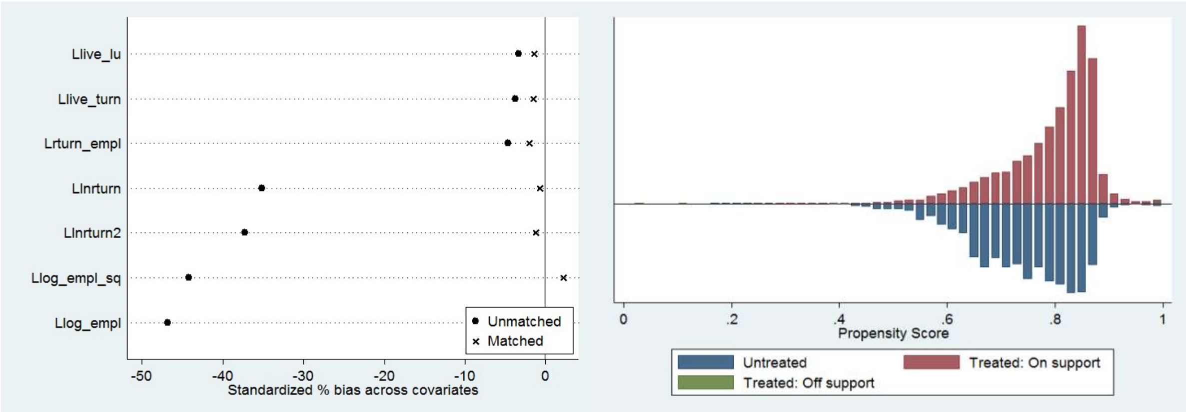
Figure A1: Matching diagnostics (continued)



4: Year 2012



5: Mature Firms



6: Large Firms (Employment > 250)

Note: * Matching diagnostic graphs for other cohorts and periods are not reported here, but they are available on request.

Table A3: UK subsidy and private R&D intensity:

(ATTs based on ten-neighbour PSM by sub-periods and years)

Period/Year	PSM (10N)	Mean Bias (%)	Median Bias (%)	Balance (%)	Pseudo R^2	Observations on common support
1998-2012	.0301*** (.0013)	0.4	0.2	2.7	0.000	Untreated: 14,989 Treated: 179,533
1998-2007	.0405*** (.0011)	0.9	1.0	4.8	0.000	Untreated: 9,731 Treated: 94,285
2008-2012	.0131*** (.0023)	0.5	0.6	4.1	0.000	Untreated: 5,258 Treated: 85,214
1998	.0421*** (.0041)	0.7	0.5	8.2	0.001	Untreated: 1,062 Treated: 6,636
1999	.0540*** (.0048)	1.1	0.9	12.1	0.003	Untreated: 946 Treated: 5,990
2000	.0591*** (.0024)	0.7	0.7	7.0	0.001	Untreated: 1,752 Treated: 5,991
2001	.0375*** (.0102)	1.0	1.3	7.4	0.001	Untreated: 417 Treated: 6,951
2002	.0232*** (.0071)	0.8	0.3	10.5	0.003	Untreated: 556 Treated: 9,096
2003	-.0556*** (.0166)	1.4	0.4	20.0	0.007	Untreated: 240 Treated: 7,603
2004	-.0093 (.0111)	1.1	1.4	7.2	0.001	Untreated: 371 Treated: 9,380
2005	.0560*** (.0038)	3.0	1.3	12.4	0.003	Untreated: 1,144 Treated: 10,719
2006	.0170*** (.0042)	3.9	2.3	16.9	0.005	Untreated: 1,216 Treated: 14,657
2007	.0242*** (.0033)	3.8	2.6	14.5	0.005	Untreated: 2,021 Treated: 16,776
2008	.0493*** (.0032)	1.7	1.4	13.8	0.003	Untreated: 2,598 Treated: 12,990
2009	-.0564*** (.0094)	1.3	0.9	12.0	0.003	Untreated: 522 Treated: 17,285
2010	.0013 (.0058)	0.3	0.3	5.3	0.001	Untreated: 799 Treated: 16,269
2011	.0149** (.0059)	1.0	0.7	8.3	0.001	Untreated: 786 Treated: 18,203
2012	-.0405*** (.0092)	1.2	1.3	12.2	0.003	Untreated: 552 Treated: 20,069

Notes: 10N – ten nearest neighbor matching; DR estimation results (in Table 5 in the main text) are not reproduced here. For other notes, see Table 5.

Table A4: UK subsidy and private R&D intensity:

(ATTs based on ten-neighbour PSM by firm type)

Firm type	PSM (10N)	Mean Bias (%)	Median Bias (%)	Balance (%)	Pseudo R^2	Observations on common support
Firm type by age						
Start-ups from 1998 to 2007	.0734*** (.0049)	1.2	0.7	18.8	0.006	Start-ups from 1998 to 2007
Start-ups from 2008 to 2012	.0263*** (.0061)	3.4	3.7	24.4	0.014	Start-ups from 2008 to 2012
Young1: 3 years old or less	.0481*** (.0038)	1.7	1.6	16.4	0.005	
Young2: less than 7 years old	.0197*** (.0012)	0.3	0.3	16.6	0.005	Untreated: 12,820 Treated: 144,854
Start-ups from 2008 to 2012	.0263*** (.0061)	3.4	3.7	24.4	0.014	Untreated: 1,046 Treated: 28,575
Mature: over 14 years	-.0563*** (.0028)	1.2	1.1	18.6	0.006	Untreated: 3,402 Treated: 12,571
Old: over 24 years	-.0471*** (.0029)	1.0	1.2	22.2	0.009	Untreated: 2,291 Treated: 8,405
Firm type by size						
Small: between 10 and 50 employees	.0269*** (.0016)	0.6	0.4	2.6	0.001	Untreated: 4,110 Treated: 57,545
SMEs: between 50 and 250 employees	-.0214*** (.0021)	0.4	0.2	5.9	0.001	Untreated: 3,909 Treated: 41,293
Firms in upper quartile of employment: 60 and more employees	-.0362*** (.0018)	0.6	0.7	12.5	0.003	Untreated: 7,678 Treated: 50,885
Large: 250 and more employees	-.0564*** (.0027)	1.3	1.3	18.6	0.006	Untreated: 4,266 Treated: 15,480

Notes: 10N – ten nearest neighbor matching; DR estimation results (in Table 6 in the main text) are not reproduced here. For other notes, see Table 5.

Table A5: UK subsidy and employment of R&D personnel:

(ATTs from one-neighbour PSM by sub-periods and years)

Period	PSM	Mean Bias (%)	Median Bias (%)	Balance (%)	Pseudo R^2	Observations on common support
1998-2012	.0279 *** (.0014)	2.2	2.2	7.3	0.001	Untreated: 14,830 Treated: 178,842
1998-2007	.0380*** (.0017)	3.2	3.1	11.3	0.002	Untreated: 9,637 Treated: 93,880
2008-2012	.0122*** (.0027)	1.5	1.5	8.5	0.001	Untreated: 5,193 Treated: 85,034
1998	.0857*** (.0042)	4.1	5.9	12.1	0.003	Untreated: 1,052 Treated: 6,604
1999	.1032*** (.0049)	1.2	1.3	9.5	0.002	Untreated: 937 Treated: 5,931
2000	.0681*** (.0034)	2.4	2.4	11.9	0.003	Untreated: 1,751 Treated: 5,950
2001	.0213*** (.0104)	2.0	0.4	16.4	0.005	Untreated: 402 Treated: 6,935
2002	-.0007 (.0094)	3.9	3.8	17.2	0.005	Untreated: 549 Treated: 9,059
2003	-.0446** (.0275)	1.2	1.2	19.5	0.005	Untreated: 233 Treated: 7,515
2004	.0007 (.0176)	4.7	3.5	25.7	0.007	Untreated: 362 Treated: 9,274
2005	.0473*** (.0057)	3.7	3.1	17.7	0.006	Untreated: 1,139 Treated: 10,688
2006	.0027 (.0059)	2.3	1.6	11.2	0.002	Untreated: 1,205 Treated: 14,648
2007	.0108*** (.0040)	2.3	2.2	7.3	0.003	Untreated: 2,005 Treated: 16,755
2008	.0466*** (.0030)	1.8	1.6	9.6	0.002	Untreated: 2,587 Treated: 12,947
2009	-.0376*** (.0110)	1.7	1.1	14.6	0.004	Untreated: 513 Treated: 17,256
2010	-.0105 (.0103)	5.7	5.9	26.5	0.006	Untreated: 785 Treated: 16,217
2011	-.0033 (.0094)	3.0	3.5	19.2	0.006	Untreated: 772 Treated: 18,060
2012	-.0356*** (.0115)	5.2	5.1	18.0	0.006	Untreated: 36 Treated: 20,019

Notes: The outcome variable is ln(R&D personnel intensity + 1). DR results are in line with the PSM results in terms of sign, significance and magnitude. They are not reported here, but they are available on request. For other notes, see Table 5.

Table A6: UK subsidy and employment of R&D personnel:
(ATTs based on one-neighbour PSM by firm type)

Subsample of firms	PSM	Mean Bias (%)	Median Bias (%)	Balance (%)	Pseudo R^2	Observations on common support
Firm type by age						
Start-ups from 1998 to 2007	.0594*** (.0057)	3.0	2.7	20.4	0.007	Untreated: 828 Treated: 14,300
Start-ups from 2008 to 2012	.0302*** (.0083)	1.1	0.6	13.9	0.004	Untreated: 1,008 Treated: 28,431
Young 1: 7 years or less	.0407*** (.0047)	1.7	0.7	10.5	0.002	Untreated: 1,836 Treated: 42,750
Young 2: over 7 years or below 14 years	.0173*** (.0016)	2.3	2.0	8.2	0.001	Untreated: 12,711 Treated: 144,471
Mature: over 14 years	-.0588*** (.0033)	3.2	0.8	14.3	0.004	Untreated: 3,396 Treated: 12,570
Old: over 24 years	-.0488*** (.0036)	2.4	1.0	12.0	0.003	Untreated: 2,289 Treated: 8,405
Firm type by size						
Small: between 10 and 50 employees	.0305*** (.0015)	0.7	0.7	3.5	0.000	Untreated: 4,078 Treated: 57,466
SMEs: between 50 and 250 employees	-.0159*** (.0028)	2.9	4.1	7.0	0.001	Untreated: 3,873 Treated: 41,273
Firms in upper quartile of employment: 60 and more employees	-.0351*** (.0023)	2.4	2.2	9.2	0.002	Untreated: 7,638 Treated: 50,865
Large: 250 and more employees	-.0578*** (.0030)	3.1	2.5	13.3	0.003	Untreated: 4,258 Treated: 15,476

Notes: The outcome variable is ln(R&D personnel intensity + 1). DR results are in line with the PSM results in terms of sign, significance and magnitude. They are not reported here, but they are available on request. For other notes, see Table 5.