Are "Complementary Policies" Substitutes? Evidence from R&D Subsidies in the UK

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Abstract

Governments subsidize research and development (R&D) through a mix of interdependent mechanisms, but the implications of subsidy interactions are not well understood. In this paper, I implement two quasi-experimental research designs to evaluate how the layering of innovation subsidies impacts firm R&D activity. I use funding rules and policy changes in the United Kingdom that generate exogenous variation in the cost of investing in R&D and find that direct grants and tax credits for R&D are complements for small firms but substitutes for larger firms. The effects are large. An increase in the tax credit rate enhances the effect of grant funding on small firms' R&D expenditures so much that R&D expenditures more than double. For larger firms, higher tax credit rates cut the positive effect of grant funding in half. I also show that subsidy interactions influence the *types* of innovation efforts that emerge: with increases in both subsidy types, small firms steer efforts increasingly towards developing new goods as opposed to improving existing ones. I explore the underlying mechanisms and provide evidence that the complementarity for small firms is a result of easing financial constraints. Substitution by larger firms is consistent with public resources subsidizing infra-marginal R&D expenditures. Some alternative explanations can be ruled out, such as expenditure relabelling and inelastic inputs. Accounting for subsidy interactions is important for optimal innovation policy design and doing so could substantially improve the effectiveness of public spending on R&D.

Keywords: R&D; innovation; policy interactions; difference-in-discontinuities; regression discontinuity design

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1 Introduction

Fostering innovation and economic growth is one of the most pressing economic challenges. In an effort to increase innovative activity, most advanced countries offer subsidies for research and development (R&D), comprising hundreds of billions of dollars in public expenditures each year. The economic case for government intervention is straight-forward: competitive markets undersupply innovative activity due to knowledge spillovers, since firms do not fully appropriate the benefits of their innovations (Nelson 1959; Arrow 1962).[1] A wide variety of instruments are used—such as direct grants and fiscal incentives—which are often layered on top of each other and framed as "complementary policies".[2] However, whether such policies are actually complements as opposed to substitutes depends on whether their interactions undermine or enhance efficiency.

In the first quasi-experimental evaluation of R&D subsidy interactions, I test whether direct grants and tax credits for R&D are complements or substitutes in their effects on firms' R&D investments. That is, how does the marginal effect of increasing funding from one subsidy type (grants) change with increases in funding from another subsidy type (tax credits)? There could be technical complementarities between a grant-funded project and other projects for which the firm claims R&D tax credits. Increases in tax credit rates could therefore enhance the effectiveness of grant funding. On the other hand, financial support from different public sources could be entirely interchangeable from the firm's perspective, suggesting that grants and tax credits are substitutes.

My empirical context is the UK, which offers the rare opportunity to examine multiple widely-used R&D support schemes that firms often use simultaneously but which have funding rules that generate separate sources of exogenous variation in the cost and profitability of R&D. I match firms across several datasets and implement two quasi-experimental research designs to study both small and large firms, as innovation incentives, sensitivities to cash flow shocks, and types of innovations realized may vary across the firm size distribution (Akcigit and Kerr 2018). I focus on the intensive margin, studying firms that are R&D-intensive and receiving subsidies.[3]

[1]Some firms also may face costly external finance and underinvest in R&D (Hall and Lerner 2010). External finance may be costly due to information asymmetries, for example.

[2]The terminology is common across policy fields. A search of the terms "complementary policies" in the online U.S. Government Publishing Office yields more than 20,000 results.

[3]The R&D tax credit scheme in the UK primarily affects firm behavior and innovation outcomes on the intensive margin (Dechezleprêtre, Einiö, Martin, Nguyen and Van Reenen 2016), and thus this is the most relevant margin to study. Data availability also limits my ability to examine the extensive margin.

To study small firms, I take a difference-in-discontinuities (henceforth "diff-in-disc") approach. This entails exploiting a sharp discontinuity in grant award rates (i.e., the proportion of proposed project costs that the funding agency subsidizes if the firm wins a grant) based upon a firm's size to identify the effect of higher grant awards on R&D expenditures. I then use before and after variation induced by increases in the R&D tax credit rate to identify the interaction effect (i.e., how changes in the tax credit rate impact the marginal effect of grant funding).

Studying larger firms requires a different empirical strategy due to the local nature of the diff-in-disc design. For larger firms, I use a sharp discontinuity generated by a different firm size threshold defining differential tax credit rates to identify the effect of tax credits on R&D expenditures, and then estimate the impact of grant funding on each side of the tax credit rate threshold. Calculating the difference in the grant effect below and above the exogenous tax credit rate threshold allows for a test of complementarity. Since this "difference-in-estimates" (DIE) is driven strictly by an exogenous firm size threshold defined by the tax credit policy, the DIE can serve as an estimator for testing whether grants and tax credits are complements or substitutes.

My results show that the subsidy schemes are complements for small firms but substitutes for larger firms, and the effects are economically significant. For small firms, a 10 percentage point increase in the grant award rate has no effect on R&D expenditures on its own. However, with substantial increases in tax credit rates, the grant effect becomes large and positive, such that R&D expenditures more than double. Expenditures on R&D increase by 154 percent on average. I show that the increase in R&D expenditures reflects an actual increase in R&D activity as measured by increases in R&D employment, to ensure that the measured effects are not just due to firms relabelling spending or increasing wages. I also rule out that the effect is driven by increasing returns to total subsidies—which would be reflected by R&D expenditures being convex in total subsidies—concluding that the positive interaction effect arises due to subsidy complementarity.

The results are entirely flipped for larger firms. I first estimate the impact of higher tax credit rates alone using a standard regression discontinuity design. The tax credit policy that generates an exogenous decrease in the cost of investing in R&D for firms under a specific employment threshold has a large, positive impact on R&D expenditures. This is consistent with the findings of Dechezleprêtre et al. (2016), who estimate the UK's tax credit policy effects using a similar identification strategy but different data. These estimates do not account for subsidy interactions, though. Doing so by estimating the DIE demonstrates that—while higher tax credit rates have a positive impact independently—they also *dampen* the positive effect that direct grants have on R&D expenditures for these larger firms. The effect of direct grant funding on R&D expenditures on its own is also positive, but this positive effect of grants is significantly lower for firms that are just under the threshold setting higher tax credit rates relative to those that are just over it. The difference is substantial: increasing tax credit rates cuts the positive effect of grants in half. The negative, large, and statistically significant difference in the marginal effect of grant funding at the tax credit rate threshold indicates that the two subsidies are substitutes.

I also examine how subsidy interactions steer the *types* of innovation efforts that firms pursue, as the composition of research influences long-run economic growth (Akcigit and Kerr 2018; Akcigit, Hanley and Serrano-Velarde 2017a). Understanding whether certain subsidy types are better suited for fostering different types of outcomes is also useful for firms' innovation strategies. I show that subsidy complementarity enhances small firms' efforts towards developing new goods and services (i.e., horizontal innovations) as opposed to improving existing goods and services (i.e., vertical innovations). It also increases the probability that small firms produce new or significantly improved goods as opposed to processes.[4] Whether this enhances long-run economic growth depends on whether horizontal or vertical innovations are the stronger engine of growth (Segerstrom 2000). For larger firms, the substitution effect is entirely accounted for by reductions in applied research, whereas the subsidy interaction actually has a very small positive impact on basic research.

What mechanisms can explain why these subsidies are complements for small firms and substitutes for larger firms? One explanation of subsidy complementarity is that small firms have binding financial constraints related to high fixed costs and indivisibilities. Investing in R&D may entail acquiring new equipment or even building an entirely new lab. Indivisible costs such as these can create barriers to undertaking or expanding projects if they are very large (Greenhalgh and Rogers 2010). Consistent with this theory, I show that the positive interaction effects are much higher for firms that are more likely to be financially constrained as proxied by their age and financial measures. Subsidy interactions also enhance small firms' investments specifically in expensive and indivisible inputs such as advanced machinery and equipment as well as land and buildings. These findings suggest that the use of both subsidy types helps small firms overcome barriers associated

[4]Process innovations involve the introduction of new processes for making or delivering goods and services.

with large, indivisible costs. I rule out alternative explanations, such as expenditure relabelling.

For larger firms, I show that subsidization of infra-marginal expenditures (i.e., expenditures that would have been privately profitable even without additional subsidies) can explain why higher tax credit rates reduce the marginal effect of grants. Increases in tax credit rates may not induce additional investment if larger firms do not face binding financial constraints. If subsidies are used interchangeably, increases in either subsidy type simply increases the proportion of total expenditures that is subsidized, decreasing the marginal return to both subsidy types due to diminishing returns. I show that the substitution effect is indeed entirely accounted for by reductions in internally-financed R&D expenditures. Alternative explanations can be ruled out.

This paper overcomes several identification challenges in order to estimate the causal effect of R&D subsidy interactions. Selection bias is the most obvious concern: innovative firms are more likely to win grant competitions and receive tax credits. Funding agencies also may select projects based upon perceived potential for success. In the case of tax credits, firm-level variation is often limited when tax rules apply to all firms, thus leaving variation to be determined by endogenous firm choices. Public investments and policy changes are also likely to coincide with unobserved factors that influence innovation activities, such as where scientific opportunities are increasing. Identifying the interaction of two endogenous policies is complicated further by firms selecting into both policies. Funding eligibility rules often align and thus cannot be used to identify the effects of either policy independently. The quasi-experimental research designs that I employ use sources of exogenous variation that are distinct for direct grants and tax credits so that the causal effect of their interaction is identified.

This paper makes four main contributions. First, it documents complementarity and substitution relationships of different types of R&D subsidies for small and larger firms.[5] In doing so, it contributes to two related literatures evaluating R&D subsidy programs and fiscal incentives using quasi-experimental designs. Most recently, Howell (2017), Azoulay, Graff Zivin, Li and Sampat (2018), Bronzini and Iachini (2014), and Einiö (2014) provide quasi-experimental evidence that direct R&D subsidy programs have positive impacts on firm outcomes, and Agrawal, Rosell and

[5]Complementarities among innovation policies have been discussed in other papers, but the causal interaction effect has not yet been estimated. For instance, Milgrom and Roller (2005) tests for complementarities in obstacles to innovation as proxies for policy, and Bérubé and Mohnen (2009) use matching methods to study the impact of grants on firms that receive tax credits.

Simcoe (forthcoming), Guceri and Liu (2019), Dechezleprêtre et al. (2016), and Bøler, Moxnes and Ulltveit-Moe (2015) use quasi-experimental methods to study R&D tax credits.[6] No papers, to my knowledge, study both direct grants and tax credits in a quasi-experimental setting.

Second, the roles of tax policy and public spending on innovation are important topics in public economics. The results of this paper may be particularly useful for studies on optimal R&D policy design (e.g., Akcigit, Hanley and Stantcheva (2017b)). There is also increasing attention in the endogenous growth literature regarding the implications of firm heterogeneity, especially across firm size and research composition (Akcigit and Kerr 2018; Akcigit et al. 2017a). Despite the importance of innovation for economic growth, there is limited empirical work in this area using micro-level data to understand firm heterogeneity. Examples of empirical papers highlighting the importance of heterogeneity in the innovation context include Howell (2017), Bronzini and Iachini (2014), and Dechezleprêtre et al. (2016), who explore firm size implications in their evaluations of R&D subsidies, and Bloom and van Reenen (2007), Bloom, Sadun and van Reenen (2012), and Bloom, Mahajan, McKenzie and Roberts (2013) who focus on management practices.[7]

Third, policy interactions are common in many economic settings, but there is limited, well-identified evidence of their effects. This paper therefore may be of interest to other fields for which policy interactions are prevalent, such as in labor, development, health, and environmental economics.[8] Evidence is typically limited due to the difficulty in finding separate sources of exogenous variation for multiple instruments.

Lastly, the results of this paper are important for policy. Accounting for complementarity and substitution between subsidy schemes in policy design could substantially improve the effectiveness of public spending on R&D. Innovation has long been recognized as a central driver of economic growth (Romer 1990; Aghion and Howitt 1992 1998), but understanding how to stimulate innova-

[6]Other studies on R&D grants include Lerner (2000), Wallsten (2000), Jacob and Lefgren (2010), Bronzini and Piselli (2016), and Takalo, Tanayama and Toivanen (2013). David, Hall and Toole (2000) survey earlier literature. Furthermore, Bloom, Griffith and van Reenen (2002), Wilson (2009), and Moretti and Wilson (2017) examine R&D tax incentives at the macro- or state-level. Rao (2016) studies R&D tax credits taking an instrumental variables approach and Bloom and van Reenen (2013) also use tax credit changes as instruments to study how the U.S. tax credits impact knowledge spillovers.

[7]Other studies drawing attention to firm size and innovation include Cohen and Klepper (1996), Klepper (1996), Kortum and Lerner (2000), Rosen (1991), and Samila and Sorenson (2011). A related literature examines how subsidies drive innovation in clean or dirty innovations. For instance, see Acemoglu, Aghion, Bursztyn and Hemous (2012), Acemoglu, Akcigit, Hanley and Kerr (2016), and Aghion, Dechezleprêtre, Hemous and Martin (2016).

[8]There is a literature examining whether information interventions and market-based tools are complementary (Duflo, Dupas and Kremer 2012; Ashraf, Jack and Kamenica 2013; Dupas 2009), and on the complementarity of programs impacting labor supply (Inderbitzin, Staubli and Zweimuller 2016; Autor and Duggan 2003).

tion with policy remains a challenge that is particularly urgent amidst the productivity slowdown experienced by most of the developed world since the mid-2000s. Direct grants and tax credits are two of the most popular instruments that governments use to subsidize R&D. Studying their effectiveness and interactions is critical for designing more efficient policy. Complementarity of subsidies for small firms suggests that these firms are currently under-subsidized, whereas subsidy substitution by larger firms suggests that these firms are over-subsidized, at least on the intensive margin. Although extrapolation of the results should remain cautious due to their local nature, similar policy designs and interdependencies exist in many other contexts.

The remainder of this paper is organized as follows. Sections 2 and 3 detail the institutional setting, empirical strategies, data, validity of research designs, and results for the small and large firm analyses, respectively. Section 4 explores the mechanisms underlying the main results and rules out some alternative explanations. The paper concludes in Section 5.

2 Small Firms: Evidence from a Difference-in-Discontinuities Approach

2.1 Institutional Setting

This section describes the two public funding resources for private R&D in the UK that I examine to study small firms: Innovate UK, which provides grants through competitions, and the R&D Tax Credit Scheme, which is available to all firms based in the UK investing in R&D. Each instrument's rules for determining subsidy rates (i.e., the proportion of expenditures funded by the grant or tax credit) induce quasi-experimental variation in the cost and profitability of investing in R&D. I discuss the key institutional features used for identification to study small firms here and reserve discussion of the features used for identification to study larger firms for Section 3.1.

2.1.1 Innovate UK: Direct Grants for Private R&D

Innovate UK, a non-departmental public body, is the UK's premier grant-awarding agency for the private sector. It has provided more than £1.8 billion to private businesses across many sectors through grant competitions since 2007, aiming to help drive productivity and economic growth

(InnovateUK n.d.). The agency runs numerous funding competitions each year. The competitions are often sector-specific or mission-driven—such as by targeting innovation in clean energy technology—but they can also be general, calling for any novel R&D innovations that have potential to make a significant impact on the UK economy. Applicants submit project proposals that detail the scope of the project, including costs, timelines, and planned activities. Once selected, awardees are subjected to finance checks, as they are required to profile costs across the duration of the funded project. All costs must be incurred and paid between the project start and end dates, and claims are subject to independent audits, reducing incentives to relabel or incorrectly document spending.

I focus on the intensive margin and test how higher grant "rates" (i.e., the proportion of the proposed project costs that is funded by the grant) impact outcomes. As such, the main feature of the program that I exploit is the funding rule that determines these rates. The Innovate UK guidelines define different funding rates that are determined by the firm's size. Higher proportions of eligible project costs are subsidized by the grants for "small firms", whereby firms are classified as small, medium, or large based upon staff headcount and either turnover or balance sheet totals following the definitions set out by the European Commission.

Small firms are classified as those with fewer than 50 employees and either a maximum turnover or balance sheet total of €10m. Although the funding rates differ based upon whether the firm is pursuing fundamental research, feasibility studies, industrial research, or experimental development, grants are ten percentage points higher for firms below the small firm threshold relative to firms above the threshold. That is, small firms are eligible for 70 percent, 70 percent, and 45 percent of total project costs to be subsidized for feasibility studies, industrial research, and experimental development projects, respectively. On the other hand, medium-sized firms, which include those just above the small firm size threshold, are eligible for funding that subsidizes 60 percent, 60 percent, and 35 percent of project costs, respectively. The only category for which this threshold does not exist is fundamental research.

2.1.2 The UK's Tax Credit Scheme

The UK's R&D Tax Relief for Corporation Tax Scheme (henceforth "R&D tax credit") was introduced in 2000 for small- and medium-sized enterprises (SMEs) and extended to large companies in 2002. The policy consists of large public expenditures: £16.5 billion in tax relief has been claimed under the R&D tax credit scheme since its launch, with £2.9 billion spent in fiscal year 2015/16 (HMRC 2017). The program design is volume-based, reducing corporate tax liabilities through an enhanced deduction of current R&D expenditures from taxable income. This differs from incremental R&D tax incentives used in some other countries, such as in the U.S, where firms benefit only if their R&D expenditures exceed some base level of previous expenditures. The main benefit that the volume-based design offers is simplicity, and thus it is widely used by firms investing in R&D despite their size or age. The UK's tax credit is also permanent, providing certainty for financial planning, unlike the R&D tax credit in the U.S., which required annual renewal until just recently.

The UK's R&D tax credit is particularly generous for SMEs: the rate of relief amounted to 150 percent of eligible expenses when it was first introduced, allowing a deduction of an additional 50 percent enhancement rate of qualifying R&D expenditures from taxable profits on top of the 100 percent deduction that applies to any expenditures. Enhanced losses can be surrendered for a payable tax credit if the SME does not earn profits, so all SMEs investing in R&D can benefit from the scheme in some way—even those that are liquidity constrained.[9] Large firms also benefit but they are eligible for lower deduction rates.

Since its inception, the deduction rate for SMEs increased through policy changes up to 200 percent in 2011 and 225 percent in 2012. This variation in the tax credit rate over time is the key feature of the tax credit scheme that I use for identifying its interaction with direct grants for *small* firms in this section. There were several other changes made to the policy in 2008 altering eligibility rules—I use these features for identification when studying larger firms and thus reserve more detailed discussion of those changes for Section 3.1.

2.2 Research Design for Small Firms

To test whether grants and tax credits are complements or substitutes for small firms, I implement a difference-in-discontinuities ("diff-in-disc") research design (e.g., Grembi, Nannicini and Troiano (2016)). The approach uses two sources of exogenous variation in R&D investment costs created by the funding rules and policy changes: 1) a discontinuity in Innovate UK grant funding rates based upon firm size (i.e., whether the firm has fewer than 50 employees), and 2) increases in tax credit rates over time. The idea is to estimate the impact of higher grant rates in the spirit of a standard

[9] On the other hand, loss-making *large* firms cannot claim a refundable tax credit (Finance Act, 2002).

regression discontinuity design (RDD), but to test how the discontinuity changes when tax credit rates increase to capture the subsidy *interaction* effect (i.e., the difference in the discontinuity).

I use employment as the running variable to determine firm size and thus eligibility for higher grant rates as a small firm. Using one running variable does not violate any assumptions associated with an RDD, and using employment rather than total assets or turnover allows for consistency throughout the paper.[10] Since grant awards are determined when the project proposal is submitted and reviewed, I use the firm's employment from one year before it receives the grant to determine treatment status.

Focusing first only on the average impact of higher grant rates induced by the Innovate UK funding rules at the small firm size threshold, I begin with the sharp RDD setup. The outcome is a function of the running variable (employment), which defines firms as small for grant rate purposes. The average treatment effect of increased grant funding is given by the estimated value of the discontinuity at the small firm 50 employee threshold as follows:

$$Y_i = \delta_0 + \delta_1 A_i^* + J_i(\gamma_0 + \gamma_1 A_i^*) + \varepsilon_i, \tag{1}$$

where Y_i is the outcome variable for firm i (primarily R&D expenditures throughout this analysis, but also other innovation outcomes as well), and J_i is an indicator for grant rate treatment status equal to 1 if firm i's (lagged) employment is less than 50 and 0 otherwise. The employment function, $A_i^* = A_i - A_c$, is normalized at the cutoff point of the running variable, A_c, and ε_i is the random error. The slope of the employment function is allowed to differ on each side of the cutoff, as is standard in RDD (Imbens and Lemieux 2008). Standard errors are clustered at the industry level here and in all subsequent regressions according to the first two digits of the Standard Industry Classification (SIC) code to adjust for potential serial correlation in errors.

The coefficient γ_0 captures the effect of a 10 percentage point increase in the grant funding rate for these firms. Due to the nature of the research design, I estimate local regressions around the cutoff point using varying sample windows, restricting the data to $A_{it} \in [A_c - h, A_c + h]$, where h represents a window around the threshold.

[10]The total assets variable is not in the dataset used to study other innovation outcomes with the UK's Community Innovation Survey nor is it in the datasets available for studying larger firms. Turnover is available but less complete than employment.

My main objective, however, is to test whether grants and tax credits are complements or substitutes. To do this, I combine this sharp RDD identifying the grant effect with before/after variation generated by the tax credit rate increase to estimate how the (grant generosity) discontinuity changes (with increased tax credit rates). Tax credit rates increased in both 2011 and 2012, and the effects are likely not experienced until at least one year later given the timing of tax credits. My sample size becomes very small once matching across datasets and narrowing the data to a tight window around the grant rate threshold, as detailed in the next section, so I create one post-treatment period for 2013 onwards.

The intuition is that the discontinuity will be larger after tax credit rates increase if tax credits and grants are complements. It will remain unchanged if they are independent and it will decrease if they are substitutes. I assume all firms in the sample apply for and receive the R&D tax credit.[11] The diff-in-disc estimates therefore capture the intent-to-treat (ITT). I implement this diff-in-disc research design by estimating the following model:

$$Y_{it} = \delta_0 + \delta_1 A^*_{it} + J_i(\gamma_0 + \gamma_1 A^*_{it}) + T_t[\alpha_0 + \alpha_1 A^*_{it} + J_i(\beta_0 + \beta_1 A^*_{it})] + \varepsilon_{it}, \tag{2}$$

where T_t is an indicator equal to 1 in the post-treatment period for an increase in tax credit generosity (from the year 2013 onwards) and all other variables are the same as above. I estimate this model for varying windows around the small firm employment threshold. The coefficient β_0 is the diff-in-disc estimator, identifying the treatment effect of increasing tax credit rates at the grant generosity threshold (i.e., the subsidy interaction effect). If the model is correctly specified, the OLS estimate of β_0 measures the difference between the post-treatment and pre-treatment value of the discontinuity in average R&D expenditures at the small firm employment cutoff point and provides an unbiased estimate of the interaction effect of R&D grants and tax credits.

Although higher-degree polynomials of the running variable are sometimes used in RDDs, recent work has shown that researchers should use only local linear or quadratic polynomials (Gelman and Imbens 2017). Higher-order polynomial models may be imprecisely estimated when the sample size is small (Lee and Lemieux 2010), as it is here. I use linear polynomials throughout most of the analyses but I show that the results are robust to higher order polynomial controls in Section 2.5.

[11]This is a reasonable assumption for these firms—the tax credit has been in place for a number of years. It is generous and salient, and conversations with small firms suggest that they use it.

2.3 Data and Summary Statistics for Small Firms

Data sources and preparation.—I use four data sources to study small firms. First, Innovate UK's Transparency Database provided publicly contains information on all grants ever given through the program. It includes details such as the total amount awarded, grant competition title and year, total project cost, legal status of firm, and project status. It also includes unique company registration numbers (CRNs), which enable matching to the other firm-level datasets. Second, Bureau van Dijk's Financial Analysis Made Easy (FAME) database provides balance sheet information for about 13 million UK and Irish companies. The FAME dataset includes the main outcome of interest—R&D expenditures—as well as other information required for determining firm size.

The Innovate UK and FAME databases are the primary sources I use for studying small firms, but I also enhance these data with other sources in order to explore the types of innovations that these firms pursue and the underlying mechanisms of their behavior. Since FAME does not detail the types of innovation investments that firms make or the outcomes that are achieved, I match these data to the UK's Business Enterprise Research and Development (BERD) and Community Innovation Survey (CIS) databases, which are provided by the UK's Office of National Statistics. The BERD data provides more details on how firms allocate R&D expenditures, which I describe in more detail in Section 3.3, since it's the primary source of R&D data used to study larger firms. The CIS is a bi-annual survey of up to 16,000 enterprises covering information on innovation activities, such as the types of innovations that they pursue.[12] Finally, in order to calculate each firm's distance to the grant-making agency headquarters in London, I use a public dataset providing all latitudes and longitudes of UK postcodes to geolocate each firm.

Details on how each dataset is prepared and merged can be found in Appendix A. I match 83 percent of the 15,167 observations from the full Innovate UK database to FAME over the period of 2007 through 2017. There are no meaningful differences between the unmatched and matched firms. Most of those that do not match either had missing or incorrectly specified CRNs in the Innovate UK database.

I restrict the data further in three main ways. First, I limit the sample to grants given in 2008 or later. Including outcomes from years prior to the great recession may bias the results if firms

[12]The survey follows the guidelines on innovation surveys set out in the OECD's Oslo Manual (OECD, 2005), which is the same format and procedure as other innovation surveys across Europe.

that survived differ systematically from those that did not in ways that impact innovation effort or capacity. For example, firms that survived the crisis may be particularly innovative and thus may have higher innovation outcomes compared to firms observed before the crisis. On the other hand, innovation outcome effects from grants may differ before the crisis if firms were more financially constrained, which has been shown to impact firm responsiveness to grants (Howell 2017).

Second, to ensure the results are not driven by outliers, I trim the sample by dropping the top and bottom 5 percent of the R&D investment distribution. This addresses the concern that innovation investments vary significantly across firms and can be highly volatile over time (Bronzini and Iachini 2014). Third, as discussed further in subsequent sections, I limit the data to varying windows around the small firm employment threshold given the local nature of the research design.

Descriptive statistics.—Table I presents descriptive statistics of the final prepared datasets, covering firm-year observations when firms receive grants from 2008 through 2017. All nominal financial variables are converted to 2010 real prices using the World Bank's Consumer Price Index for the UK. The full sample includes 12,128 grant awards given from 2008 through 2017 to 8,227 unique firms. I use three sub-samples of firms of varying window sizes around the grant generosity threshold based on the firm's employment level: fewer than 100 employees (wide window), 10 to 90 employees (midrange window), and 20 to 80 employees (narrow window). There are 1,180 Innovate UK grants given to firms in the wide window and 635 given to firms within the narrow window.

The sample sizes become small once matched to the R&D data, since not all firms report R&D expenditures. In the wide window sample including firms under 100 employees, for example, there is R&D expenditure data for 196 of the 1,180 observations, with 133 observations above the small firm threshold and 63 observations below it. In the narrowest window used, there is R&D expenditure data for 124 of the 635 observations, with 83 observations above the grant threshold and just 41 below it. Although the use of large, detailed datasets offers the benefit of providing enough data to implement a diff-in-disc research design, matching to the R&D expenditure data and narrowing the sample around the threshold reduces the sample size substantially.

Nonetheless, I show that the results are robust to both wide and narrow windows around the cutoff as well as numerous other specifications and falsification tests (see Section 2.5), and the results are replicable using different data on R&D expenditures (see Section 3). The main concern about sparse R&D data is that there could be selection bias if reporting differs systematically around the threshold. I discuss how this does not appear to be the case in the next section.

[TABLE I ABOUT HERE]

2.4 Validity of Research Design for Small Firms

Using sources of exogenous variation that do not align between subsidy types allows for causal interpretation of the subsidy interaction effect under two key identifying assumptions. First, in order for the RDD component of the research design to be valid, the firm size cutoff determining grant rates must be exogenous and firms must not perfectly manipulate the running variable (Lee 2008). In this setting, savvy firms could purposely maintain firm size just below the threshold in order to take advantage of more generous grant rates. Manipulation also may occur if there are other existing policies that create substantial benefits for firms at this exact threshold. It also could be that Innovate UK gives more grants to small firms relative to those just above the threshold. These scenarios would be problematic as they would imply either that the threshold is not exogenous or that firms just under the grant generosity threshold differ from those just above the threshold in systematic ways that are unobservable and correlated with the outcome.

I employ four empirical tests of randomization at the small firm employment threshold to provide confidence that the continuity assumption is satisfied and that the distribution of predetermined variables is smooth around the cutoff. For all four tests, firms receiving Innovate UK grants and with fewer than 100 employees are included in the sample. First, in Figure I, Panel A, I inspect the density of firms by firm size to check whether there is a spike in the density just under the small firm threshold, as would be expected if firms manipulate the running variable (either in response to the funding rules or any other policy generating different incentives for firms just below this threshold). I find no visual evidence of"bunching" around the 50 employee cutoff. Second, to formalize this, I conduct a McCrary density test (Figure I, Panel B). The discontinuity estimate (log difference in density height at the threshold) is 0.3328 with a standard error of 0.2298, suggesting that there is no statistically distinguishable discontinuity in the firm size distribution at the threshold.

[FIGURE I ABOUT HERE]

Third, treated and untreated firms around the threshold should be similar in observed characteristics as a consequence of randomization (Lee 2008). I verify this by showing that there are no statistically significant differences in the mean values of several covariates for treated and untreated firms around the cutoff point (see Table II).[13] I test for differences in total assets, current liabilities, cost of sales, credit limit, the total cost of the proposed project, and the total number of grants received from 2008 through 2017. There are no statistical differences. Fourth, I reinforce this conclusion by estimating the RDD model of Equation 1 with these covariates as dependent variables. The results are presented in Appendix Table B.1, showing that the discontinuity is statistically zero in all cases.

[TABLE II ABOUT HERE]

I do not limit the sample to firms that also report R&D expenditures when conducting these tests, as the primary concerns are that any firm applying for and receiving an Innovate UK grant may try to manipulate firm size, or that the Innovate UK agency favors small firms. However, since not all firms report R&D, I also examine the histogram and conduct a McCrary density test for samples conditional on R&D expenditure reporting to ensure that there is no selection in reporting around the 50 employee threshold. No differences are detected.

The results of these four empirical tests provide assurance that the threshold is exogenous and firms do not strategically manipulate their firm size. It also strongly suggests that there are no other confounding policies. Nonetheless, I also manually reviewed a large sample of UK programs and policies to ensure that there are no others that impose a 50 employee threshold or provide an incentive for firms to manipulate their size around this cutoff. For instance, in France, many labor laws start to bind on firms with 50 or more employees, and thus there is significant bunching (Garicano, Lelarge and Van Reenen 2016). Details on the sample that I examined are provided in Appendix Table B.2. Fortunately, while the UK tends to offer special benefits and fiscal incentives to small- and medium-sized firms (SMEs), such policies and programs typically are not specific to small firms. Firms above the small firm threshold and up to the medium-sized firm threshold are typically eligible. When there are benefits specifically for smaller firms, the thresholds and

[13] I am unable to use data prior to policy implementation because this grant generosity threshold existed since Innovate UK's inception. Nonetheless, continuity in observables around the threshold persisting throughout the program provides strong evidence of randomization and a lack of firm size manipulation.

definitions differ relative to the ones set by Innovate UK.

The second identification assumption for estimating the causal interaction effect is that there must not be any other policy changes during this time that *differentially* affect firms just below and above the 50 employee cutoff. The effect of the tax credit alone cannot be identified in this setting, as estimates are confounded by many other policy changes and trends, but its *interaction* with grant funding is identified as long as other changes do not differentially affect firms around the grant rate threshold.

The tests above and investigation of UK policies imply that this holds: the absence of such a threshold in any other policy or program indicates that *changes* in those policies or programs would not differentially affect firms around the 50 employee threshold. I conduct one final empirical test for reassurance and estimate the diff-in-disc model of Equation 2 with the covariates as dependent variables. The results provided in Appendix Table B.3 indicate that there are no detectable differences in the discontinuity for these variables, indicating that it is unlikely that there are other policies changing during this time that differentially affect firms around the cutoff.

One final concern is that effects in later years could be driven by increased R&D data reporting over time. This could occur if more firms invest in R&D as the tax credit increases. Indeed, the R&D data coverage does improve from 2008 through 2017. This is only a problem for identification if reporting improves *differentially* around the 50 employee cutoff. I examine the trends in R&D reporting for firms in my sample, and increases in reporting for firms just below the 50 employee threshold follow the same patterns as increases in reporting just above the 50 employee threshold.

To summarize, these empirical tests and the investigation of UK policies provide confidence in the identifying assumptions for the diff-in-disc research design. The 50 employee threshold appears to be exogenous, as firms just below and just above the cutoff are similar, and firms do not manipulate their size. This validates the cross-sectional RDD component of the approach. Furthermore, as no other changes in policies appear to differentially affect firms just below and above the cutoff, the causal effect of the subsidy interaction is also identified.

2.5 Main Results for Small Firms

Average Grant Effect.—Before examining subsidy interactions, I begin with an analysis of the average effect of increased grant rates over the entire time period. Figure II plots average R&D

expenditures against increasing levels of employment for the years 2008 through 2017. To construct Figure II, I assign firms to evenly-spaced groups based upon employment and compute the mean R&D expenditures for observations within each group. I plot mean R&D expenditures against employment, superimposing a best-fit line on the points as a visual aid and allowing for the slope of the line to differ on each side of the firm size threshold determining differential grant rates.

[FIGURE II ABOUT HERE]

Figure II illustrates that R&D expenditures appear to increase in employment on average for firms under the threshold and benefitting from higher grant rates, whereas there is no clear relationship above the threshold. It does not appear as though there is a jump at the discontinuity, but rather a kink, if anything. Results from estimating this effect in the RDD model of Equation 1 are consistent with the graphical analysis (see Table III). There is no statistically significant discontinuity in R&D expenditures at the cutoff. When using the wide window sample (Column 1, Table III), the funding rule appears to induce a positive kink in the slope of R&D investments relative to employment for firms under the threshold. However, this is just barely statistically significant, and the estimates are statistically zero once narrowing the window around the threshold. The diff-in-disc estimator is statistically zero in all cases.

[TABLE III ABOUT HERE]

Policy Interaction Effects.—I now turn to the primary results capturing the R&D subsidy interactions, beginning with a graphical analysis. Figure III plots average R&D expenditures for evenly-spaced groups of firms below and above the grant generosity threshold, but separately for the period before the tax credit increases (2008-12) in Panel A and after (2013-17) in Panel B. Illustrating this heterogeneity tells a very different story relative to Figure II. Higher grant rates for small firms just below the threshold appears to have no impact on R&D expenditures before 2013. However, after the tax credit rate increases, R&D expenditures increase substantially at the firm size threshold determining higher grant rates. This suggests that the higher grant rate had no effect on R&D expenditures without the additional increase in tax credit rates, but higher grant rates have positive and large effects once combined with a substantial tax credit rate hike.

[FIGURE III ABOUT HERE]

Results from estimating the diff-in-disc model of Equation 2 confirm that the grant effect on its own is statistically zero, but the interaction effect is positive, large, and statistically significant (see Table IV). These results imply that the two subsidy types are complements for these small firms. Columns 1 to 3 present the results when using wide and more restricted sampling windows around the grant generosity threshold. I also include additional control variables for preciseness: firm age, distance to London, total grant funding awarded to the firm's competition in which it received a grant, and total grant funding awarded in the year. When considering the most conservative case (Column 2), the results indicate that the increase of both grant and tax credit rates enhance R&D expenditures by about £2.2m on average. This is a 154 percent increase relative to the average R&D expenditures of firms in the sample.

[TABLE IV ABOUT HERE]

It is possible that increases in R&D expenditures do not reflect actual increases in R&D activity. For instance, firms may relabel ordinary spending as R&D spending or simply increase wages of existing R&D workers. I explore these possibilities in Section 4 and show that actual R&D activity does indeed increase as measured by R&D-specific employment.

2.6 Interpreting the Results as Subsidy Complementarity

One interpretation of these results is that R&D grants and tax credits are complements on the intensive margin. Increasing the tax credit rate greatly enhances the marginal effect of direct grants, and such complementarity gives rise to increasing returns. Another plausible interpretation—which must be ruled out in order to conclude that the results are indeed driven by complementarity—is that the subsidies are actually interchangeable but there are increasing returns to *total subsidies*. That is, it could be that small firms increasingly benefit from more public funding regardless of its source as opposed to benefitting from the combination of the two subsidy types.

To test this, I examine whether small firms' R&D expenditures are convex or concave in the total subsidies received. Convexity (concavity) of R&D expenditures in total subsidies would imply increasing (decreasing) returns to total subsidies. I calculate the implied tax credit amount that small firms receive based upon their R&D expenditures net of the Innovate UK grant amount, the tax credit rate applicable during that year, and the corporate tax rate that year. I add this implied tax credit to the Innovate UK grant amount to find each firm's total subsidies. Unfortunately, I do not observe other grants and direct funding that the firms receive, but this approach serves as a rough approximation.

Figure IV plots average R&D expenditures against average total R&D subsidies for evenly-sized groups of firms. In Panels A and B, the full sample of small firms receiving grants is used, and Panels C and D use the winsorized sample omitting the bottom and top 5% of the R&D expenditure distribution. Firms are grouped into 15 bins in Panels A and C and 30 bins in Panels B and D. The plots provide no indication that small firms' R&D expenditures are convex in total R&D subsidies. If anything, they are slightly concave. The coefficient on the total subsidies squared term is negative and statistically significant in all cases. This concavity suggests that the positive interaction between direct grants and tax credits for small firms is *not* explained by increasing returns to total subsidies but rather a complementarity between the two subsidy types.

[FIGURE IV ABOUT HERE]

2.7 Falsification and Robustness Tests

I conduct a number of robustness checks to ensure that the results hold under different modelling assumptions and when addressing concerns with the data. I start with a falsification test in which I set artificial cutoffs in the running variable and test whether R&D expenditures are continuous across pseudo-thresholds. The outcome should be smooth, since policies do not alter the cost of investing in R&D at these arbitrary thresholds. Statistically significant discontinuities would suggest that the main results are simply an artifact of functional form assumptions. Table V presents results when setting three different random cutoffs, using both wide and narrow windows around the thresholds. No statistically significant differences in the discontinuities are detected.

[TABLE V ABOUT HERE]

An additional concern is that the effect of grant funding simply has become stronger over time. For instance, firms may have been investing conservatively in the years immediately following the great recession. It also could be that firms surviving the great recession—making up a larger proportion of all firms in earlier years in my sample relative to later years—are less sensitive to R&D cost shocks than the average firm in later years. A related concern is that there is improved data coverage over time, and thus the lack of a grant rate effect in earlier years could be due to a lack of statistical power.

To ensure that this is not the case, I carry out a falsification test for the tax credit rate change timing by imposing artificial tax credit changes in later years. If the positive interaction effect is driven simply by grant funding becoming more effective over time or by richer R&D expenditure data in later years, there should also be statistical differences in the discontinuity in later years. The results are presented in Appendix Table B.4 when setting pseudo-tax credit change years as 2013 and 2014, and using different sub-samples of data around the grant rate threshold. There are no statistically significant effects.

I conduct several other robustness checks and provide the findings in Appendix Table B.5. I use uniform weights for the majority of the analysis, however the main diff-in-disc results are robust to placing more weight on the observations closer to the threshold, as shown by the use of triangular weights for the wide and narrow window samples in Columns 1 and 2, respectively. The results are also robust to using quadratic polynomial controls (Column 3) and cubic polynomial controls (Column 4), and to using a 1% winsorization rule rather than 5% (Column 5).

2.8 What *Types* of Innovations Emerge?

The majority of this paper focuses on R&D expenditures—a critical input into innovation—as opposed to innovation outcomes, as this is the first level at which one might expect to see an effect. I take this as the first-order variable of concern for rigorously studying the causal effect of subsidy interactions, primarily leaving the exploration of other innovation and economic outcomes for future work. Nonetheless, policymakers are interested in designing instruments that not only enhance R&D investments in general but especially those that ultimately foster innovation and growth. The impact of R&D investments on long-run productivity and growth depends on the composition of research and the types of innovations that the subsidies promote (Akcigit and Kerr 2018; Akcigit et al. 2017a; Segerstrom 2000). For example, whether public policies such as R&D investments drive growth hinges upon whether the subsidies promote horizontal (i.e., developing new goods) or vertical innovation activities (i.e., improving existing goods), and which type of innovation is the stronger engine of economic growth (Segerstrom 2000).

To briefly explore what types of innovation efforts and outcomes are enhanced by subsidy complementarity, I match the Innovate UK data to the UK's Community Innovation Survey (CIS), which provides firm-reported information related to the types of innovations that they pursue for a stratified sample of firms, including small firms. I do not limit the matching to only firms that also report R&D expenditures in order to match a sufficient sample of firms.[14] See Appendix A for more details on the dataset and matching procedure.

I estimate the effect of subsidy interactions on firm responses that proxy for whether the firm pursues horizontal versus vertical innovations using the diff-in-disc model of Equation 2. The results are provided in Appendix Table B.6, starting with wider windows around the grant rate threshold relative to the main analysis due to the small sample size but limiting the sample to firms with 10 to 90 employees in the narrowest case. There are consistently positive and large subsidy interaction effects on innovation efforts aiming to help the firm enter an entirely new market (Column 1), whereas there is a negative effect on efforts aiming to improve the quality of goods and services (Column 2). Similarly, when examining whether the firm reports producing a new or significantly improved good versus process, subsidy interactions enhance the chances that the firm produces a goods innovation (Column 3) but not a process innovation (Column 4).

Taken together, these results suggest that subsidy complementarity drives small firms to increase horizontal innovation efforts—those expanding the firm's scope as they aim to produce new products—as opposed to vertical innovations—those improving processes or the quality of existing goods and services. Whether this has an enhancing effect on long-run economic growth depends on whether horizontal or vertical innovation is the stronger engine of economic growth.

[14]This means that I use the employment figures reported in CIS for determining whether the firm falls below the grant rate threshold for these regressions, but there is no reason to believe this information is inaccurate or systematically biased, to the best of my knowledge.

3 Larger Firms: Evidence from a Regression Discontinuity

3.1 Institutional Setting

As discussed in Section 2.1, firms that qualify as SMEs benefit from much higher tax credit rates than larger firms. One twist is that the definition for what constitutes a SME under the R&D tax credit scheme is different than what constitutes a SME for all other intents and purposes in the UK. For R&D tax credit purposes only, SMEs are defined as firms with fewer than 500 employees (and either sales less than €100m or total assets less than €86m). These thresholds are double those used by the EU and the UK for defining SMEs for all other purposes. The 500 employee threshold is the primary feature that I use for identification to study larger firms. Even though firms just under 500 employees are classified as SMEs here for tax credit purposes, they are typically considered large firms, and they are most certainly much larger than the firms studied in Section 2.

3.2 Research Design for Large Firms

A different research design is required to study the interaction of R&D grants and tax credits for larger firms, as the diff-in-disc approach of Section 2 is local to small firms by construction. For larger firms, I use the 500 employee threshold of the R&D tax credit scheme in an RDD framework to identify the effect of higher tax credit rates on R&D expenditures, whereby firms under the cutoff benefit from much higher tax credit rates than those just above the cutoff.

I also use this variation for identifying the interaction of tax credits with grants by estimating the effect of direct subsidy funding on R&D expenditures separately on each side of the tax credit rate threshold and calculating the difference in the grant funding effects at the cutoff. With the "difference-in-estimates" (DIE) driven strictly by the exogenous 500 employee threshold defined by the tax credit policy, this can serve as an estimator and test of whether grants and tax credits are complements or substitutes. If the subsidies are complements (substitutes), the marginal effect of direct subsidies should be higher (lower) for firms below the tax credit threshold receiving more generous tax credits.

I estimate the following model separately for firms just below the 500 employee cutoff and those just above the cutoff in narrow windows around the threshold:

$$Y_{it} = \alpha + \beta_1 G_{it} + \mathbf{X}_{it}\phi + \gamma_t + \delta_b + \eta_p + \varepsilon_{it}, \tag{3}$$

where Y_{it}, is R&D expenditures for firm i in year t, G_{it} is firm i's direct subsidy funding amount received in year t, and γ_t are year fixed effects to control for R&D trends over time. The specification also controls for time-invariant mean differences in R&D effort with δ_b business structure fixed effects and η_p product group fixed effects, and $\mathbf{X}_{it}$ includes the running variable and firm age as controls. Standard errors are clustered by industry, defined as the first two digits of the firm's SIC.

To identify the subsidy interaction effect, I estimate the DIE by testing whether the marginal effect of direct subsidies (i.e., grant funding) for firms just under the tax credit generosity threshold is statistically different than the effect for firms just above the cutoff.[15] An alternative approach to estimating a difference in the grant funding treatment is to interact it with a dummy defining tax credit treatment, however this severely over-rejects under model misspecification, even when data are limited to narrow windows around the running variable cutoff (Hsu and Shen 2019). I therefore estimate Equation 3 separately on each side of the threshold and test whether the coefficients for the grant effect are statistically different, while still limiting the sample to a narrow window around the tax credit threshold.

Of course, grant funding is endogenous for the many reasons already discussed: unobservable information influences the firm's ability to propose R&D projects, win grant competitions, and obtain funds. This calls for a valid instrumental variable (IV) to identify the grant effect itself. However, my main objective here is to focus on the *interaction* of grant funding with tax credits, which is generated by the exogenously-determined tax credit threshold. As long as the endogeneity moves in the same direction and with a similar magnitude for firms just below and just above the tax credit rate threshold, using OLS to estimate the separate grant effects is sufficient for identifying the interaction effect at the threshold. I therefore combine the RDD with an OLS approach throughout most of this analysis, but I also provide results from an IV approach as a robustness check.

[15] I use a simple Z-test calculated as the difference of the coefficient estimates divided by the square root of the sum of each coefficient's variance.

3.3 Data

Since the Innovate UK grant scheme primarily focuses on smaller firms (or SMEs as defined in the traditional way), I use alternative measures and data for direct subsidies to study larger firms. The main data sources for studying larger firms include the UK's Business Enterprise Research and Development (BERD) database and Business Structure Database (BSD) collected by the Office of National Statistics (ONS). The BERD survey collects data on R&D expenditures and other characteristics of firms identified as actively performing R&D. A stratified sampling approach is employed using a combination of the Annual Business Survey, HM Revenue and Customs (HMRC), and CIS data to identify R&D-performing firms. The full BERD datasets begin with about 30,000 observations per year. I take a number of steps to prepare the data for analysis, such as dropping all observations with imputed values for R&D expenditures, leaving about 2,500 observations per year. Also, since the BERD datasets provide data at the reporting unit level, I aggregate the data to the enterprise level for the purposes of studying a firm's R&D activity.

I match BERD to BSD in order to determine a firm's R&D tax credit eligibility status. The BSD provides information on a small number of variables for the universe of UK firms, deriving data from the Inter-Departmental Business Registrar (IDBR), which is a live register of administrative data collected by HMRC. It includes all businesses that are liable for VAT and/or have at least one member of staff registered for the Pay as You Earn tax collection system. Although the BERD data also reports firm size, employment is measured at the reporting unit level, whereas tax credit rates are determined by firm size at the enterprise group level. The BSD datasets include enterprise-level employment. I aggregate these figures to the enterprise group level for determining whether firms have fewer than 500 employees.

For each dataset, I match firms over time to create unbalanced panels from 2009 through 2014, and I then merge the BERD and BSD data based upon unique firm identifiers. I also augment these data with calculations of the driving travel distance (in kilometers and time) between each enterprise and the central grant-funding agency in the UK, which relies on another dataset providing the latitudes and longitudes of all postcodes in the UK. The final dataset consists of about 2,000 to 2,500 enterprise groups per year. A full discussion of the data sources, preparation, and matching procedures can be found in Appendix A.

The data on R&D expenditures are broken down by the sources of financing, such as external private finance, internal private finance, or the central government. I proxy for "direct subsidies" with the amount of R&D expenditures that are funded by the central government. These can include grants, such as those allocated through funding competitions, but also other direct support mechanisms. The exact source is not identified, but importantly, the variable does not include funding received through R&D tax credits.

Appendix Table B.7 provides summary statistics of the final data used to study larger firms. One observation to highlight is that a much smaller proportion of R&D is funded by direct subsidies for these larger firms compared to small firms. About 6% of R&D expenditures are funded by the central government for firms with 250 to 750 employees on average, whereas for small firms, the Innovate UK grant alone accounts for more than 50% of R&D expenditures on average. This implies that larger firms do not rely as much on direct subsidies for supporting their innovation investments, but interestingly, they do still receive such resources.

Corroborating Small Firm Results.—An obvious concern with using different data to study larger firms is that conclusions comparing small and large firms could be an artifact of the data itself rather than differences in how they respond to incentives. To ensure that this is not the case, I first corroborate the small firm results with these data. There are drawbacks to using these datasets for the small firms' main analysis, since BERD does not comprehensively cover small firms as it does larger firms. The data owners interpolate missing values for small firms and identifying which observations have interpolated versus real data is not clear in some years. Nonetheless, corroborating the small firms' results with these data can provide confidence that differences in findings for larger firms are not driven by differences in measurement or data collection procedures.

Appendix Table B.8, Panel A provides the results from estimating the diff-in-disc model of Equation 2. Slightly larger windows of firms around the grant rate threshold are required due to sample size and additional noise created by the data interpolation, but the sign and order of magnitude of the estimates are consistent with those found in Section 2. The subsidy interaction effect on R&D expenditures is positive, large, and statistically significant. In fact, the magnitude of the effects is even larger here than when using the FAME R&D expenditure data, despite having similar levels of average R&D expenditures. Statistical significance is lost in the narrowest sub-sample of firms, but the point estimate remains large and positive. For completeness, Appendix Table B.9 provides falsification tests using these data, imposing pseudo-thresholds for grant rate treatment status and for varying windows of data. There are no statistical differences, as expected.

One benefit of using this data is observing the source of finance for R&D. As one final test of whether subsidy interactions enhance small firms' private R&D expenditures, and to further explore the types of private expenditures that are most affected, I estimate the impacts separately for internally-financed R&D (i.e., R&D expenditures financed by the firm's own funds as well as subsidiaries or the parent company) and externally-financed R&D (i.e., expenditures funded by other private businesses in the UK and non-governmental organizations). Panel B of Appendix Table B.8 reports the results. The entirety of the complementarity effect can be explained by increases in R&D expenditures financed internally by the firm, confirming that subsidy interactions have positive effects on the firms' own innovation investments.

3.4 Validity of Research Design for Large Firms

The 500 employee cutoff defining firms as SMEs for R&D tax credit purposes generates a sharp discontinuity in the cost of investing in R&D. The exclusion restriction is satisfied since the thresholds are double those of many other policies providing incentives and benefits that may affect firm behavior, which are typically set according to the standard SME definition. From 2008 onwards, there are no other policies or programs that define firm size thresholds aligning with those of the R&D tax credit scheme that would confound estimating a LATE around the employment cutoffs.

Nonetheless, I conduct three empirical tests of the identifying assumptions to provide further confidence in the validity of the research design. I start by checking whether the running variable is manipulated around the tax credit generosity cutoff of 500 employees. Bunching just under the threshold would suggest that firms are able to manipulate firm size to take advantage of the tax credit benefits, and savvy firms exhibiting this behavior may differ systematically from those just above the threshold, confounding a comparison of the two groups of firms. Figure V presents two tests for this type of manipulation. Visual inspection of the histogram in Panel A indicates that there is no obvious increase in the density of firms just below the cutoff, and the results from the McCrary test plotted in Panel B confirm that this is the case. The log-difference is not statistically significant at the threshold.

[FIGURE V ABOUT HERE]

Third, I test for continuity in observable covariates around the threshold in pre-policy years to provide confidence that the cutoff was randomly selected. Table VI presents results when testing for statistical differences using t-tests in covariate means around the threshold in years prior to the tax credit rate threshold implementation. There are no statistical differences in variables such as turnover, direct subsidy levels, and expenditures on different types of R&D, suggesting firms just below and above the threshold in pre-policy years are similar. There are also no statistical differences in the main outcome variable of interest—R&D expenditures. These tests provide confidence that the tax credit generosity threshold can be interpreted as randomly assigned.

[TABLE VI ABOUT HERE]

3.5 Main Results for Large Firms

Impact of Tax Credits Only.—Before turning to the interaction of the two types of subsidies, I begin by estimating the effect of higher tax credit rates only. Figure VI plots average R&D expenditures for evenly-sized groups of firms against total enterprise group employment. Firms with 250 to 750 employees are included for the post-policy period (2009 through 2014). Once again, I assume all firms in these datasets identified as being R&D intensive apply for and receive the R&D tax credit, so the effects represent an intent-to-treat.

There is a clear discontinuity in average R&D expenditures at the 500-employee threshold, indicating that the higher tax credit rates have a large, positive effect. To confirm, I estimate a regression discontinuity model (following the form of Equation 1) using the 500-employee threshold for determining treatment status. I estimate this for the years 2009 onwards, when the 500 employee threshold is in place, and also for pre-policy years 2002 through 2008, when the 500 employee threshold did not exist. The results for varying windows around the tax credit rate threshold are provided in Appendix Table B.10 including linear and quadratic trends of the running variable. The findings indicate that there is a large, positive impact of higher tax credit rates at the 500 employee threshold in the post-policy period (Panel A), and as expected, no statistical difference at the threshold in pre-policy years (Panel B). Considering the midrange window that includes firms with 250 to 750 employees and when using linear polynomials, the treatment effect is £1.07m, reflecting a 55% increase in R&D expenditures relative to the pre-policy sample mean of £1.9m.

This result provides us with two pieces of important information. First, the tax credit policy appears to have large, positive effects on average R&D expenditures for these firms when studying the policy on its own. But these estimates ignore the potential interactions with other subsidies for R&D, of course. Second, while this estimate is lower than those from Dechezleprêtre et al. (2016), who use different data and a different running variable, the large, positive effects of the policy are consistent with their main findings.

[FIGURE VI ABOUT HERE]

Subsidy Interaction Effects.—Turning to subsidy interactions, Table VII provides the main results of estimating the effect of direct subsidies on R&D expenditures by Equation 3 separately on each side of the threshold determining which firms are eligible for higher tax credit rates. Findings are presented for various-sized windows around the tax credit threshold. The effects of direct subsidies for firms under the tax credit rate threshold are presented in odd-numbered columns and in even-numbered columns for firms over the threshold. The final row provides the difference in the direct subsidy estimates below and above the tax credit threshold, or the DIE estimates.

The results indicate that direct subsidies have a positive and statistically significant effect on R&D expenditures in all cases. However, the effect for firms just below the threshold—those receiving more generous tax credits—is much *lower* than it is for those above the threshold. The negative interaction effect is both statistically and economically significant. In the most conservative case (Columns 3 and 4), higher R&D tax credit rates cut the positive effect of grants in half. The dampening effect of higher tax credit rates on the marginal effect of grants indicates that the two subsidies are substitutes for these larger firms.

[TABLE VII ABOUT HERE]

One potential concern is that the estimated effects of direct subsidies are larger than what one might expect, which is most likely due to endogeneity bias. However, the scale of the grant effect does not alter the interpretation of the subsidy *interaction effects* (i.e., the DIE estimates)—which are driven only by the exogenous discontinuity in tax credit rates—as long as the endogeneity is similar on both sides of the threshold. In the next section, I vet this assumption and show that it appears to hold.

I also examine the impacts on the types of R&D investments that these larger firms make to test whether the subsidy interactions have implications for their scope of research. The results are provided in Appendix Table B.11 for when estimating the effects separately for expenditures allocated to basic research, applied research, and experimental development. The results show that higher tax credit rates significantly reduce the marginal effect of grants on applied research expenditures, accounting for most of the substitution. The marginal effect of grants on basic research actually increases just slightly, although by much less than than the decrease in applied research. There are no statistical differences in the effects on expenditures in experimental development.

3.6 Falsification and Robustness Checks

This section conducts several robustness checks to provide further confidence in the main results. I begin by using employment data from preceding years to determine a firm's tax credit treatment status. Eligibility for the higher tax credit rate formally requires that firms fall under the threshold for two consecutive years. I use only the current year's employment data in the main analysis because the panel is very unbalanced. Including only firms with multiple, consecutive years of data significantly reduces the sample size. Nonetheless, I check that the results hold when defining tax credit treatment based upon the firm's preceding years of employment with these smaller samples. The results are presented in Table VIII. Columns 1 and 2 define tax credit treatment based upon the firm's preceding year's employment, Columns 3 and 4 define it based upon both the current year and preceding year's employment, and Columns 5 and 6 define it based upon the current year and two preceding years' employment. Firms with 250 to 750 employees are included (i.e., the results are comparable to the midrange window results of Table VII). The results hold in all cases and even become stronger—the impact of direct subsidies is cut by more than half here across all three sets of results—suggesting that the main estimates are conservative, if anything.

[TABLE VIII ABOUT HERE]

Second, I check whether the effect of grants is continuous across arbitrary pseudo-thresholds where there is no difference in the tax credit rates. These results are presented in Table IX. No differences are detected. Third, in Appendix Table B.12, I provide estimates from regressions using increasing flexibility of the employment running variable up to third degree polynomial controls. The results are nearly identical across specifications, consistently indicating that the effect of direct subsidies is significantly smaller for firms benefitting from higher tax credit rates.

[TABLE IX ABOUT HERE]

Finally, although using OLS to estimate the effect of direct subsidies on each side of the tax credit threshold is sufficient for capturing the interaction effect if the endogeneity of direct subsidies is similar for firms in a tight window around the tax credit threshold, I employ an instrumental variable (IV) strategy to further corroborate the results. The research design validity tests already demonstrate that firms just below and above the tax credit threshold appear to be very similar and that there is no strategic bunching, suggesting that the endogeneity is highly unlikely to differ at the threshold. Nonetheless, using an IV strategy can provide additional insight into whether this holds—that is, a valid IV should shift the estimates for the impact of direct subsidies by roughly the same amount and in the same direction on each side of the threshold if the endogeneity is about the same, and the first-stage results should be similar on each side of the threshold.

I propose a new IV that uses the *interaction* of two sources of variation in direct subsidy levels: 1) total direct subsidy funding allocated to a firm's industry each year ("technology funding budget"), and 2) the driving distance between the firm's headquarters and the UK's primary grant-making agency measured in kilometers ("distance"). Using the interaction of these two variables as the instrument as opposed to each variable independently as separate instruments overcomes exclusion restriction violations. It allows for the *main* effects of each variable to be included in the first and second stages as controls, thus directly addressing the exclusion restriction concerns that would otherwise arise from using either of them on their own, while the interaction itself is used as the IV. The approach follows a strategy first proposed by Card (1995) and used more recently in Bettinger, Fox, Loeb and Taylor (2017).

To justify the use of the interaction term as the instrument, first consider each variable on its own. They both satisfy the relevance condition but most likely violate the exclusion restriction. Higher technology budgets are positively correlated with the level of funding each winning firm receives, as there is more funding available.[16] However, funding agencies' decisions regarding which industries to support are endogenously determined by other governmental priorities as well as market trends. These factors are likely correlated with unobservable firm characteristics that affect R&D decisions. Similarly, the distance between the firm and the funding agency may be negatively correlated with grant award levels, as firms located farther away are less likely to have frequent in-person meetings with the agency. Having more meetings over time and building better relationships with funders due to proximity may provide closer firms with a competitive advantage.

But relationship-building is unlikely the only influence through which distance affects grant funding. Distance is also correlated with innovation spillovers, for instance. The agency is located in London, which is ranked as the most innovative city in the UK (Forth and Billingsley 2017). Knowledge spillovers could affect the firm's innovation capacity and thus its ability to win grants. Distance from the grant-making agency is also a function of firm choices about where to operate, which may be related to unobservable characteristics that determine a firm's R&D effort.

To alleviate the exclusion restriction concerns that arise if one were to use these two variables as instruments, my instrument is constructed as their *interaction*. The main effects of both variables therefore can be used as controls in the first and second stages of the regression with only the interaction serving as the excluded instrument. The interaction captures a compounding effect and is negatively correlated with direct subsidies. Higher technology budgets increase award amounts but heterogeneously across firms. The positive effect should be weaker for firms that are located farther away from the grant-making agency, as firms closer to the agency have an even higher incentive to set up meetings and build relationships when more funding is available.

Causal interpretation still involves an exclusion restriction, but using the interaction IV while including main effects as controls requires much weaker identifying assumptions than if both variables were used as IVs. The exclusion restriction now requires that: 1) any other mechanism through which firm distance from the agency affects firm behavior is constant over time, and 2) any other mechanism causing firm behavior to differ over time affects firms homogenously with respect to their distance from the agency. Potential violations of this exclusion restriction are highly implausible. For instance, a violation would occur if firms change location in response to the amount of grant funding that is available to their industry in a particular year. This is extremely

[16] Similar measures have been used as IVs in previous studies of innovation grants, such as in Wallsten (2000).

unlikely, not only because firms relocate rarely, but also because the availability of grant funding is an unreasonable motivation for changing firm location. A more plausible violation would be if the grant-making agency decides how much funding to allocate to an industry based on potential outcomes. For this to formally violate the exclusion restriction, the decision rule would need to give systematically different weights to firms based on their distances from the agency's office. I am not aware of any rules or norms in the decision-making process that would induce this, besides the possibility of preferential treatment for firms that interact with the agency in more frequent in-person meetings. Using the interaction variable as the excluded instrument, I can control for this directly through the main effect of distance.

Table X presents the results from taking the IV approach with variations in how the IV is constructed. Columns 1 and 2 use the interaction of the firm's driving distance from the funding agency measured in kilometers and total subsidies allocated to the firm's industry each year as defined by the full 5-digit SIC. Columns 3 and 4 use the firm's driving distance measured in time (minutes) interacted with industry annual funding defined by the 5-digit SIC. Columns 5 and 6 use distance measured in kilometers but interacted with total subsidies for the firm's industry based only on the first 2 digits of the SIC. Appendix Table B.13 provides the first stage results.

There are two key takeaways. First, the story is consistent with the OLS results: the impact of direct subsidies is consistently cut in half for firms under the tax credit threshold.[17] Second, there is no statistical difference in the effect of the IV on direct subsidies below and above the threshold in the first-stage regressions, suggesting that the endogeneity of direct subsidies is similar for firms in a tight window around the threshold. The IV satisfies the relevance condition, as it's highly statistically significant across all specifications and the F-statistics for the excluded instrument are large, but the difference in first stage effects are mostly statistically indistinguishable from zero.[18] The use of OLS combined with the RDD therefore appears sufficient for identifying the subsidy interaction effect.

[17] Note that the estimates increase substantially across all specifications relative to the OLS results. One may be concerned that they are still contaminated by significant bias and that the effect of direct subsidies is not identified, however the estimates move in the same direction and of a similar magnitude in all cases, which is the primary concern for identifying the interaction effect.

[18] One exception is that the difference becomes just barely statistically significant at the 10% level in Columns 3 and 4. The F-statistics are also just slightly below 10 in Columns 5 and 6—they are 9.96 and 9.67, respectively—although they are above 20 in all other specifications.

[TABLE X ABOUT HERE]

4 Mechanisms

The main result of this paper—that direct grants and tax credits for R&D are complements for small firms and substitutes for larger firms on the intensive margin—has important policy implications for policy design regardless of the mechanism through which it occurs. Nonetheless, understanding the source of the effects can yield additional insight. In this section, I provide suggestive evidence that subsidy complementarity is consistent with small firms having binding financial constraints, and the substitution by larger firms is consistent with public funds subsidizing infra-marginal expenditures. There are some alternative explanations that can be ruled out.

4.1 What Explains Subsidy Complementarity Subsidies for Small Firms?

4.1.1 Indivisibilities and Easing Financial Constraints

The leading explanation for why subsidies are complements for small firms is that these firms have binding financial constraints. Consider the following scenario. A firm that invests in multiple R&D projects has a new idea. It applies for and wins a grant that funds 50% of the new project's planned expenditures, which increases the firm's total R&D expenditures. The firm continues to claim tax credits on other R&D projects that are not funded by the grant. There is a new piece of machinery or equipment that would be helpful for increasing the efficiency of all projects, however the firm is financially-constrained. An unexpected increase in the tax credit rate allows the firm to make the large purchase, enhancing not only the success of the projects funded by tax credits but also the one funded by the grant, increasing the marginal effect of grant funding.

I provide two sets of results that suggest the subsidy complementarity for small firms can be explained by overcoming financial constraints, and particularly those associated with large, indivisible investments. First, I examine whether firms that appear to be more constrained as proxied by their age and current financial standing are more responsive to the subsidies than those that are less constrained. That is, I estimate the main diff-in-disc model for R&D expenditures separately for firms that are under and over the median levels of three variables proxying for such constraints: firm age, current liabilities, and current assets. Table XI provides the results. The point estimates, although imprecise, are much higher for younger firms as well as for those with higher current liabilities and lower current assets (i.e., those that are more likely to be financially-constrained). This conclusion is consistent with recent findings in the literature that point to grants inducing an additionality effect for small firms that is associated with overcoming financial constraints (Howell 2017). In the current context, subsidy complementarities—as opposed to a single instrument—appear to be important for firms to overcome financial constraints.

[TABLE XI ABOUT HERE]

Furthermore, indivisibilities give rise to sizable fixed costs, which may be difficult for financially-constrained firms to fund without support if the cost of capital is too high. Setting up new laboratories, manufacturing facilities, or office spaces requires significant upfront capital. These investment requirements are also indivisible—machines and equipment come in specific sizes and work spaces must be rented for a given time period. Testing whether subsidy complementarities impact expenditures specifically related to invisible investments can shed further light on whether such complementarity is explained by financial constraints.

I estimate Equation 2 using three dependent variables from the BERD and CIS data that proxy for large, indivisible costs: a dummy variable equal to one if the firm made investments in advanced machinery and equipment for the purposes of current or future innovation (from the CIS database), and firm expenditures on land and buildings or equipment and machinery (from the BERD dataset). The results are provided in Table XII. They suggest that subsidy complementarity enhances these expenditures on both the extensive and intensive margins. Higher subsidies increases the probability that small firms invest in advanced machinery and equipment by about 52 percent (Column 1), and there are positive and statistically significant effects on the levels of expenditures as well (Columns 2 and 3).

[TABLE XII ABOUT HERE]

4.1.2 Alternative Explanations

R&D Input Relabelling.—One concern is that higher tax credits provide firms with an incentive to relabel ordinary spending as R&D spending in order to reap more substantial benefits (Hall and

Van Reenen 2000). In other words, the estimated positive effects may be a function of firms classifying spending differently as opposed to actually increasing their innovation activities. Increases in expenditures also may just reflect increases in wages rather than actual R&D activity.

To assess these hypotheses, I test whether there is a systematic (negative) change in non-R&D inputs that offsets positive changes in R&D inputs. Appendix Table B.14 provides the results from estimating the diff-in-disc model using data from BERD on R&D employment versus non-R&D employment. There is a positive and statistically significant increase in R&D employment (which are large in magnitude compared to the sample mean of the dependent variable), but a very small, negative, and statistically insignificant effect on non-R&D employment. Since labor is the primary R&D expenditure that qualifies for tax credits in the UK, this provides confidence that the subsidy complementarity effect is not simply a symptom of R&D input relabelling. Increases in R&D expenditures reflect actual increases in R&D activity. The positive effect on R&D labor also confirms an actual increase in R&D activity rather than just an increase in wages.

Learning.—Another potential explanation for finding positive effects for subsidy interactions is learning-by-doing, as knowledge and experience in production can drive productivity growth and increase returns to capital (Arrow 1962; Lucas 1988). In the present context, learning-by-doing could be a factor if firms improve in their abilities to apply for, and secure, subsidy funds over time, or if firms learn to more creatively exploit the combination of subsidy schemes. This could explain the results if small firms are more experienced, and thus more acquainted with the subsidy programs, than larger firms. This is not the case. Examining firms with fewer than 100 employees, those under the 50 employee threshold receiving Innovate UK grants have a median age of 12 years and those above it have a median age of 19 years.

Absorptive Capacity.—Relatedly, accumulated R&D efforts over time enhance a firm's absorptive capacity. Firms tend to invest in R&D not only to pursue a specific project or the development of a particular product, but also to build their broader skills and capabilities, which enables them to better assimilate knowledge (Cohen and Levinthal 1989). This affects how they benefit from knowledge spillovers, which may induce complementarities in a firm's R&D efforts. However, larger and more experienced firms are more likely to have developed greater absorptive capacities, which are built over time and grow as a function of R&D investments (Cohen and Levinthal 1990). If absorptive capacity plays a role in subsidy interactions for the firms studied here, complementarities in larger firms rather than small firms would be expected, as they have more resources and have operated for longer time periods, on average.

4.2 What Explains Subsidy Substitution for Larger Firms?

4.2.1 Subsidization of Infra-Marginal Expenditures

The most plausible explanation of subsidy substitution by larger firms is that public funds are subsidizing infra-marginal expenditures (i.e., they are displacing investments that the firm would have made anyway without the additional funding). It could be that higher tax credit rates do not induce more R&D investment because these larger, R&D-intensive firms do not have binding financial constraints. Higher tax credit rates will therefore increase the proportion of expenditures that are funded by subsidies rather than increase total expenditures, displacing other sources of finance. With diminishing returns, the marginal return to each subsidy type decreases.

One way to evaluate this hypothesis is to estimate the marginal effect of grants on the firm's privately-financed investments in R&D as opposed to total R&D investments. Table XIII provides results when using internally-financed R&D expenditures (Columns 1 and 2) and R&D expenditures financed by other external private sources (Columns 3 and 4) as the dependent variables. All of the substitution is accounted for by reductions in the firm's own internal financing of R&D (Columns 1 and 2). This implies that infra-marginal expenditures are indeed subsidized by public sources. The subsidy interaction actually seems to have a small, positive effect on the firm's ability to secure external private finance.

[TABLE XIII ABOUT HERE]

4.2.2 Alternative Explanations

Inelastic R&D Inputs.—Another channel through which substitution could occur is inelastic supply of R&D inputs. If larger firms are constrained (as they may have been immediately following the great recession), they may temporarily scale-down some projects as they increase efforts in projects tied to grant funding. Innovation inputs such as capital investments and R&D labor may therefore shift from one project to another without increasing the firm's net innovation investments.

For an inelastic supply of inputs to explain the findings, the substitution effect should not persist over time (Lach 2002). I estimate Equation 3 for firms under and over the tax credit generosity threshold using only later years in the sample, omitting the years just following the 2008 financial crisis. Appendix Table B.15 provides the findings when using data from only years after 2010 (Columns 1-2) and only after 2012 (Columns 3-4). The substitution effect indeed persists.[19] This suggests that the inelasticity of R&D inputs is an unlikely explanation for the substitution behavior.

R&D Input Relabelling—Section 4.1 discusses how one form of R&D input relabelling can explain complementarity, but a different form of relabelling can also explain substitution. The tax credit in the UK primarily applies to non-capital expenditures on R&D, which are largely comprised of labor costs. With increased tax credit rates, firms have an incentive to relabel capital R&D expenditures as non-capital R&D expenditures. The total amount of R&D spending reported will remain the same when this occurs, but the marginal return to grants will decrease because the proportion of expenditures that are subsidized increases.

For this to explain the results, the effect of subsidy interactions on *non-capital* R&D expenditures should be positive, offsetting negative effects on capital R&D expenditures. I show that this is not the case (see Appendix Table B.16). The substitution effect is entirely explained by negative effects on non-capital expenditures and there is no effect on capital expenditures, suggesting that input relabelling is an unlikely explanation.

Political Capture and Information Asymmetries.—A final channel through which substitution of subsidies could occur is related to the objective function of the funding agencies. Grant-making agencies often face political pressure to successfully allocate funds. This can distort preferences in favor of projects that are most likely to succeed, but these projects are also most likely to be privately profitable (and thus pursued by the firm even without the subsidy). As such, public funding could displace private spending that would have occurred even without the subsidy. Similarly, even if funding agencies are seeking to fund marginal projects, they are unlikely to fully observe attributes that determine whether certain projects will be successful and thus profitable. The firm has better insight regarding inputs like management quality. The informational asymmetry between

[19] The DIE loses significance when using only post-2012 years due to a much smaller sample size, but the direction and magnitude are nearly identical to the main estimates.

firms and the funding agency also can lead to the subsidization of infra-marginal projects.

In my empirical setting, however, all firms receive direct subsidies. There is no comparison of firms receiving grants to those that do not receive grants. Furthermore, the R&D tax credit in the UK is a general subsidy and it is not tied to any specific project of the firm, or types of firms. The UK government cannot discriminate in how tax credits are distributed besides through the differential rates that are determined by firm size. There is no central agency making the decision to provide tax credits only to projects that it predicts may be profitable and thus politically attractive. There is also no evaluation or selection process where information asymmetries could impede the ability to identify marginal projects. Political capture and information asymmetries are therefore highly implausible explanations of subsidy substitution in this setting.

5 Conclusion

This paper studies how the interactions of tax credits and direct grants for private R&D impact firms' innovation investment behavior. I show that the two subsidies are complements for small firms but substitutes for larger firms on the intensive margin for UK firms. The effects are significant both economically and statistically: increasing both grant and tax credit rates more than doubles R&D expenditures of small firms, but increasing tax credit rates for larger firms cuts the positive effect of grants in half. Subsidy interactions also affect the types of innovations that emerge. Complementarity increases small firms' investments in horizontal innovations, and the substitution for larger firms leads to reductions in applied research as opposed to basic research.

These results have important implications for policy. Direct grants and tax credits are the two most popular tools that policymakers use to support private investment in innovation, but their effects on firm R&D investment activities are not independent, and thus accounting for these subsidy interactions in optimal R&D policy design could substantially enhance the efficiency of public spending on R&D. My results suggest that, at least when examining the intensive margin, subsidies for R&D in the UK appear to be sub-optimally low for small firms due to binding financial constraints, but larger firms are currently over-subsidized. Increases in the R&D tax credit are subsidizing infra-marginal expenditures for larger firms. This is not to say that larger firms should not be subsidized at all—knowledge spillovers associated with their investments justify some public support—but these firms do not appear to have binding financial constraints in comparison to small firms, for which additional public spending would be justified.

The findings presented in this paper should be interpreted with a few caveats in mind. The tax credit components of the estimates are intent-to-treat effects, although it is highly likely that these firms are treated given their reporting of R&D investments and the salience of the UK tax credit scheme. Furthermore, the local nature of the research designs limits the generalizability of the results. The findings may provide insight for policy design in other countries, given the popularity of direct grant and tax credit schemes, but extrapolation to firms of sizes beyond those studied here and to firms in other countries must be taken cautiously. Finally, this paper focused on the intensive margin, which is where the UK's tax credits have been shown to matter most. Subsidy interaction effects and the policy implications that follow ultimately depend on whether the same complementarity and substitution effects also exist on the extensive margin, and whether the effect on the extensive or intensive margin dominates.

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MAIN TEXT TABLES

Table I: Innovate UK Grant Award and Outcome Variables, Descriptive Statistics

	Full Sample	Wide Window (< 100 Employees)	Midrange Window (10 to 90 Employees)	Narrow Window (20 to 80 Employees)
Panel A: Grant Awards				
No. of Unique Grants	12,128	1,180	897	635
No. of Unique Firms	8,227	850	651	475
Panel B: Funding Levels				
Grant Amount (£000s)	£304.26	£711.57	£763.35	£751.41
	(£2,693)	(£5,976)	(£6,567)	(£6,937)
Total Project Cost Funded (%)	65.3%	58.1%	57.5%	57.1%
	(23.5%)	(22.8%)	(22.0%)	(22.3%)
No. of Observations				
Panel C: Outcome Variable				
R&D Expenditures (£000s)	£7,860.77	£1,302.29	£1,433.49	£1,477.73
	(£17,940)	(£1,906)	(£1,991)	(£2,022)
No. of Observations	825	196	155	124

Notes: Panel A provides information on the number of grants and awardees and Panels B and C provide mean values and standard deviations (in parentheses) of funding levels and R&D expenditures. Sample includes data from Innovate UK and Bureau van Dijk's FAME final prepared datasets used in the small firms analysis. Only firm-year observations when grants are received from 2008 to 2017 are included.

Table II: Covariate Balance Around Small Firm Employment Threshold

	Means			Observations	
	<50	≥50	Difference	<50	≥50
Total assets (£ms)	£18.91	£16.77	-£2.14	671	507
Current liabilities (£ms)	£10.48	£8.88	-£1.60	661	505
Cost of sales (£ms)	£74.12	£12.08	-£62.04	408	412
Credit limit (£ms)	£0.53	£0.41	-£0.12	580	483
Total cost of project (£000s)	£1,071	£737	-£335	668	501
Number of grants received (2008-17)	2.50	2.48	-0.02	673	507

Notes: Includes Innovate UK and FAME data for firms with fewer than 100 employees receiving grants from 2008 through 2017. Financial variables are converted to real 2010 GBP. Table shows covariate balance between treated and untreated firms around small firm employment threshold. There are no statistically significant differences between covariate means, providing confidence in "randomization" of the grant generosity threshold. This also holds when limiting the sample to those with R&D expenditure data.

Table III: Impact of Higher Grant Rate on R&D Expenditures, Small Firms

	Wide Window (< 100 Empl.) (1)	Midrange Window (10 to 90 Empl.) (2)	Narrow Window (20 to 80 Empl.) (3)
1[employment < 50]	466.22	301.57	1175.66
	(550.26)	(577.15)	(1211.80)
Employment * 1[employment < 50]	25.61**	-3.00	-29.99
	(12.35)	(28.43)	(52.39)
Sample mean for dependent variable	£1,302	£1,433	£1,478
No. of Observations	196	155	124

Notes: Dependent variable is firm total R&D expenditures (£000*s*). First order polynomials of the (centered) running variable (employment) are included separately for each side of the threshold. Other controls include firm age, driving time to London, total grant funding awarded to the firm's competition, total grant funding awarded in the year, and year fixed effects. Standard errors are clustered by industry. Asterisks denote *p <0.10, **p <0.05, ***p <0.01.

Table IV: Diff-in-Disc Results for Effect of Subsidy Interactions on R&D, Small Firms

	(1)	(2)	(3)
	Wide Window (< 100 Empl.)	Midrange Window (10 to 90 Empl.)	Narrow Window (20 to 80 Empl.)
1[year = post 2012] *1[employment < 50]	2440.69*	2208.39**	2880.13*
	(1203.60)	(981.07)	(1489.18)
1[year = post 2012] *1[employment < 50] *employment	24.17	86.75	43.03
	(30.18)	(61.64)	(66.88)
1[employment < 50]	-1258.47	-1185.34	-929.8
	(899.02)	(772.91)	(848.49)
Sample mean for dependent variable	£1,302.28	£1,433.49	£1,477.73
No. of Observations	196	155	124

Notes: Dependent variable is firm total R&D expenditures (£000*s*). First order polynomials of the (centered) running variable are included separately for each side of the threshold. Specifications also include dummies for size threshold, size threshold by centered employment, tax credit increase treatment year (equal to one if the year is post-2012), and treatment year by centered employment. Other controls include firm age, driving time to London, total grant funding awarded to the firm's competition, total grant funding awarded in the year, and year fixed effects. Standard errors are clustered by industry. Asterisks denote *p <0.10, **p <0.05, ***p <0.01.

Table V: Diff-in-Disc Pseudo-Threshold Falsification Tests, Small Firms

	(1) Wide Window (+/- 70 Employees)	(2) Midrange Window (+/- 30 Employees)
A. Employment Threshold of 30		
1[year = post 2012] * 1[employ < 30]	31.55	-519.35
	(870.41)	(1076.94)
No. of Observations	196	105
B. Employment Threshold of 70		
1[year = post 2012] * 1[employ < 70]	-105.71	-402.7
	(840.74)	(711.69)
No. of Observations	242	134
C. Employment Threshold of 90		
1[year = post 2012] * 1[employ < 90]	-3209.6	-1985.42
	(2283.12)	(1574.56)
No. of Observations	236	115

Notes: Dependent variable is firm total R&D expenditures (£000*s*). First order polynomials of the (centered) running variable (employment) are included separately for each side of the threshold. Specifications also include dummies for size threshold, size threshold by centered employment, tax credit increase treatment year (equal to one if the year is post-2012), and treatment year by centered employment. Other controls include firm age, driving time to London, total grant funding awarded to the firm's competition, total grant funding awarded in the year, and year fixed effects. Standard errors are clustered by industry. Asterisks denote *p <0.10, **p <0.05, ***p <0.01.

Table VI: Pre-Policy Covariate Balance Around Tax Credit Generosity Threshold, Larger Firms

	Means			Observations	
	<500	$\geq$ 500	Difference	Obs. $<$ 500	Obs. $\geq$ 500
	(1)	(2)	(3)	(4)	(5)
R&D Expenditures (£000s)	£1,141.79	£986.54	£155.25	1,350	924
Proportion of R&D Expenditures Funded	4.0%	4.0%	0.0	1,350	924
Turnover (£000s per employee)	£197.01	£154.91	£42.10	1,350	924
Expenditures on Applied Research	£400.90	£350.51	£50.39	1,350	924
Expenditures on Basic Research	£84.60	£58.55	£26.05	1,350	924

Notes: Descriptive statistics provide means of covariates during the *pre-policy* period for firms around the tax credit generosity threshold. Only firms with 250 to 750 employees and receiving direct subsidies are included. There are no statistical differences in pre-policy covariate means, providing confidence in "randomization" of the tax credit generosity threshold.

Table VII: Interaction Effect of Grants and Tax Credits on R&D Expenditures, Larger Firms

	Wide Window (150 to 850)		Midrange Window (250 to 750)		Narrow Window (350 to 650)	
	$<$500	$\geq$ 500	$<$500	$\geq$ 500	$<$500	$\geq$ 500
	(1)	(2)	(3)	(4)	(5)	(6)
Direct Subsidies (£000s)	2.539***	6.910***	3.229***	6.610***	2.287***	7.901***
	(0.400)	(1.534)	(0.607)	(1.366)	(0.220)	(1.855)
No. of Observations	1,506	761	848	635	488	409
Difference at Threshold	-4.371***		-3.381**		-5.614***	
	(1.585)		(1.495)		(1.868)	

Notes: Dependent variable is total R&D expenditures. The first row of each column reports the estimated average effect of direct subsidies using OLS in separate regressions below and above the tax credit generosity threshold for varying sub-samples of data around the threshold. All specifications also include controls for employment, age, distance to funding agency HQ, total value of subsidies allocated to each industry-year, and fixed effects for year, business structure, product group, and industry. Standard errors are clustered by industry. Asterisks denote *p <0.10, **p <0.05, ***p <0.01.

Table VIII: Interaction Effect Using Lagged Employment Values, Larger Firms

Employment year(s) used to define tax credit treatment	One Year Lag		Current + One Year Lag		Current + Two Year Lags	
	<500	≥ 500	<500	≥ 500	<500	≥ 500
	(1)	(2)	(3)	(4)	(5)	(6)
Direct Subsidies (£000s)	2.786***	8.691***	2.505***	6.772***	2.689***	7.508***
	(0.619)	(2.007)	(0.369)	(1.748)	(0.479)	(2.088)
No. of Observations	860	588	657	440	510	300
Difference at Threshold	-5.905***		-4.267**		-4.819**	
	(2.100)		(1.787)		(2.142)	

Notes: Dependent variable is total R&D expenditures. The first row of each column reports the estimated average effect of direct subsidies using OLS in separate regressions below and above the tax credit generosity threshold for firms receiving direct subsidies and with 250 to 750 employees. Columns 1 & 2 define tax credit treatment based upon the firm's preceding year's employment level being less than 500. Columns 3 & 4 define it based upon both current and the preceding year's employment level, requiring both years' employment levels to be less than 500. Columns 5 & 6 define tax credit treatment based upon current and two preceding years' employment being less than 500. All specifications also include controls for employment, age, distance to funding agency HQ, total value of subsidies allocated to each industry-year, and fixed effects for year, business structure, product group, and industry. Standard errors are clustered by industry. Asterisks denote *$p<0.10$, **$p<0.05$, ***$p<0.01$.

Table IX: Pseudo Threshold Falsification Tests, Larger Firms

	Below Threshold (1)		Above Threshold (2)
A. Pseudo Threshold of 200			
Direct Subsidies (£000s)	2.717***		1.891***
	(0.084)		(0.622)
No. of Observations	5,385		766
Difference at Threshold		0.826	
		(0.628)	
B. Pseudo Threshold of 250			
Direct Subsidies (£000s)	2.058***		2.654***
	(0.370)		(0.360)
No. of Observations	2,011		688
Difference at Threshold		-0.596	
		(0.516)	
C. Pseudo Threshold of 750			
Direct Subsidies (£000s)	7.142***		6.615*
	(1.338)		(3.437)
No. of Observations	493		278
Difference at Threshold		0.527	
		(3.688)	
D. Pseudo Threshold of 800			
Direct Subsidies (£000s)	6.465***		8.232**
	(1.175)		(3.854)
No. of Observations	407		276
Difference at Threshold		-1.767	
		(4.029)	

Notes: Dependent variable is total R&D expenditures. Estimates report the average effect of direct subsidies from separate regressions below and above artificially-imposed thresholds. Firms with 0 to 400 employees are included in Panel A. Firms with 50 to 450 employees are included in Panel B. Firms with 550 to 950 employees are included in Panel C. Firms with 600 to 1000 employees are included in Panel D. All specifications include controls for employment, age, distance to funding agency HQ, total value of subsidies allocated to each industry-year, and fixed effects for year, business structure, product group, and industry. Standard errors are clustered by industry. Asterisks denote *$p<0.10$, **$p<0.05$, ***$p<0.01$.

Table X: IV Regressions, Interaction Effect of Grants and Tax Credits, Larger Firms

	Primary IV Approach		Alternative IV #1		Alternative IV #2	
	(1)	(2)	(3)	(4)	(5)	(6)
	<500	≥ 500	<500	≥ 500	<500	≥ 500
Direct Subsidies (£000s)	5.352***	10.252***	6.025***	10.535***	5.305***	10.957***
	(0.375)	(1.294)	(0.541)	(1.542)	(0.533)	(1.249)
No. of Observations	848	635	848	635	848	635
Difference at Threshold	-4.900***		-4.510***		-5.652***	
	(1.347)		(1.634)		(1.358)	
IV = Distance * total SIC subsidies	x	x				
IV = Travel time * total SIC subsidies			x	x		
IV = Distance * subsidies in 2-digit SIC					x	x

Notes: Dependent variable is total R & D expenditures. Estimates report the average effect of direct subsidies from separate two-stage least squares regressions below and above the tax credit generosity threshold. Firms with 250 to 750 employees are included. The excluded instrument in Columns 1 & 2 is the interaction of (i) the firm's driving distance in kilometers to the UK's primary funding agency HQ and (ii) the total value of subsidies allocated to the firm's industry-year. The IV in Columns 3 & 4 uses travel distance in time (minutes) rather than distance. The IV in Columns 5 & 6 measures the firm's industry-year subsidies by the first two-digits of the SIC rather than full SIC. All specifications include the main effects of each variable interacted in the IV. All specifications also include controls for employment, age, and fixed effects for year, business structure, product group, and industry. Standard errors are clustered by industry. Asterisks denote *p <0.10, **p <0.05, ***p <0.01.

Table XI: Estimates Below and Above Median of Financial Constraint Proxies, Small Firms

Data Sub-Sample:	Below Median of Financial Constraint Variable (1)	Above Median of Financial Constraint Variable (2)
Panel A: Firm Age		
1[year = post 2012] * 1[employment <50]	3045.69**	2573.12**
	(1093.71)	(1107.74)
No. of Observations	128	130
Panel B: Current Liabilities		
1[year = post 2012] * 1[employment <50]	-425.93	3544.81
	(1772.37)	(2356.56)
No. of Observations	129	129
Panel C: Current Assets		
1[year = post 2012] * 1[employment <50]	2149.29*	734.2
	(1177.59)	(1248.29)
No. of Observations	129	129

Notes: Dependent variable is total R&D expenditures (£000s). Regression estimates are for firms below (Column 1) and above (Column 2) the median firm age (Panel A), current liabilities (Panel B), and current assets (Panel C) of firms receiving grants with fewer than 150 employees. All controls are the same as in the baseline regressions. Standard errors are clustered by industry. Asterisks denote *p <0.10, **p <0.05, ***p <0.01.

Table XII: Effect of Subsidy Interactions on Large Indivisible Investments, Small Firms

Dependent Variable:	Advanced Machinery Investment (y/n)	Land & Buildings Expenditures	Equipment & Machinery Expenditures
	(1)	(2)	(3)
1[year = post 2012] *1[employment < 50]	0.520*	100.05*	294.02**
	(0.30)	(55.08)	(124.70)
Sample mean for dep. variable	0	£22,000	£70,000
No. of Observations	171	262	262

Notes: Dependent variables are different proxies for large, indivisible fixed costs often associated with starting a new R&D project. In Column 1, the dependent variable is an indicator variable for whether the firm invested in advanced machinery and equipment for the purposes of current or future innovation (from the CIS dataset). In Columns 2 and 3, the dependent variables are firm R&D expenditures on land and buildings or equipment and machinery (from the BERD dataset). First order polynomials of the (centered) running variable (employment) are included separately for each side of the threshold. Specifications also include dummies for size threshold, size threshold by centered employment, treatment year (equal to one if the year is post-2012), and treatment year by centered employment. Standard errors are clustered by industry. Asterisks denote *$p < 0.10$, **$p < 0.05$, ***$p < 0.01$.

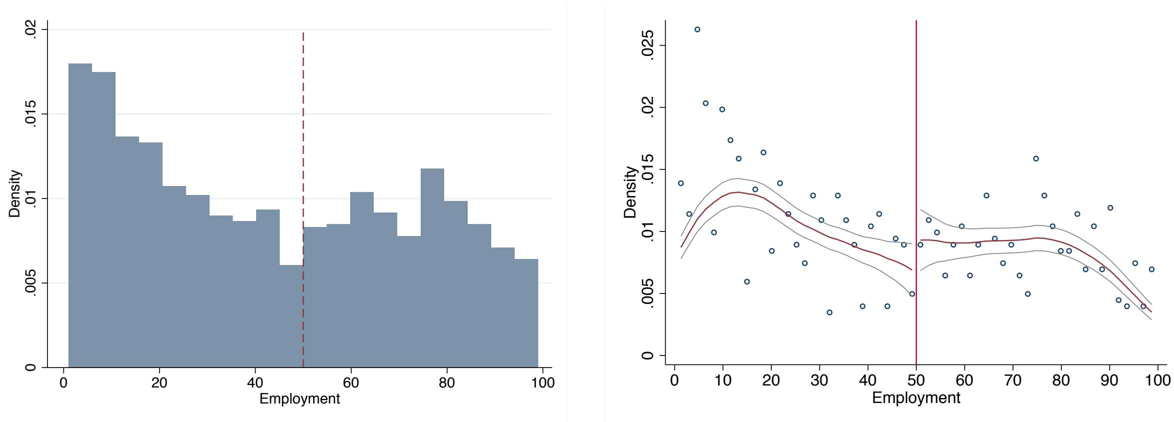
Table XIII: Subsidy Interaction Effects by Source of Financing, Larger Firms

Dependent Variable:	Internal Financing of R&D		External Private Financing of R&D	
	(1)	(2)	(3)	(4)
	<500	≥500	<500	≥500
Direct Subsidies (£000s)	1.699***	5.620**	0.329***	0.101*
	(0.542)	(1.146)	(0.089)	(0.051)
No. of Observations	848	635	848	635
Difference at Threshold	-3.921***		0.228**	
	(1.268)		(0.103)	

Notes: Dependent variables are proxies for internal and external private finance for R&D. In Columns 1 & 2, internal financing of R&D is the firm's expenditures on performing R&D funded by the firm's own funds as well as other overseas organizations, including subsidiaries or the parent company. In Columns 3 & 4, external private finance is the firm's expenditures on performing R&D funded by private businesses in the UK and other organizations besides the government, such as private non-profits. The first row of each column reports the estimated average effect of direct subsidies below and above the tax credit generosity threshold for firms with 250 to 750 employees. All specifications include controls for employment, age, distance to funding agency HQ, total value of subsidies allocated to each industry-year, and fixed effects for year, business structure, product group, and industry. Standard errors are clustered by industry. Asterisks denote *p <0.10, **p <0.05, ***p <0.01.

MAIN TEXT FIGURES

Figure I: Evidence of No Manipulation at the Small Firm Employment Threshold

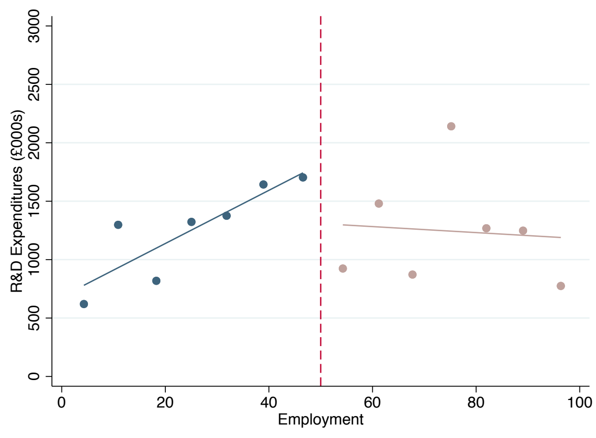


(a) Histogram Based Upon Employment

(b) McCrary Density Test Based Upon Employment

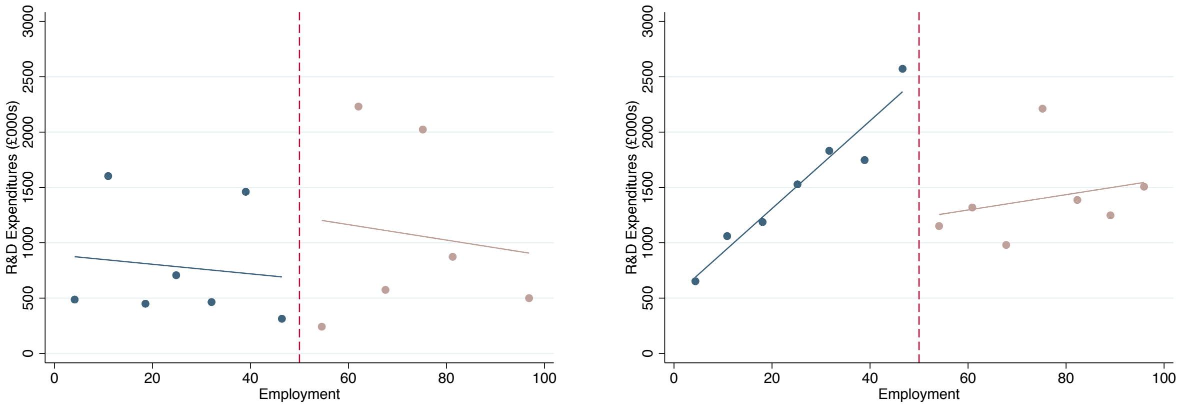
Note: Histogram and McCrary test for discontinuity in distribution density of total employment at the small firm employment threshold. Sample includes firms with fewer than 100 employees. Log difference in density height of 0.3328 with a standard error of 0.2298.

Figure II: Average Impact of Increased Grant Generosity on Firm R&D Expenditures



Note: Data points represent average R&D expenditures for evenly-spaced bins of firms receiving Innovate UK grants with fewer than 100 employees. The running variable (employment) is on the x-axis.

Figure III: Impact of Policy Interactions on R&D Expenditures

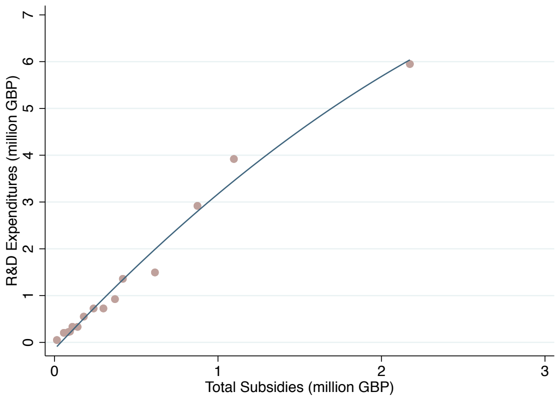


(a) Before Tax Credit Increase

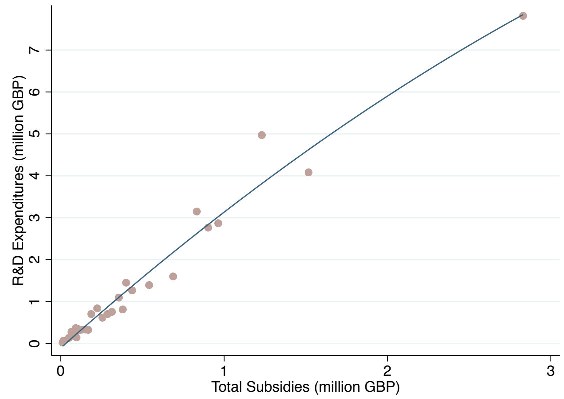
(b) After Tax Credit Increase

Note: Data points represent average R&D expenditures for evenly-spaced bins of firms receiving Innovate UK grants with fewer than 100 employees before (Panel A) and after (Panel B) the tax credit rate increases. The y-axis measures average R&D expenditures. The running variable is employment and on the x-axis.

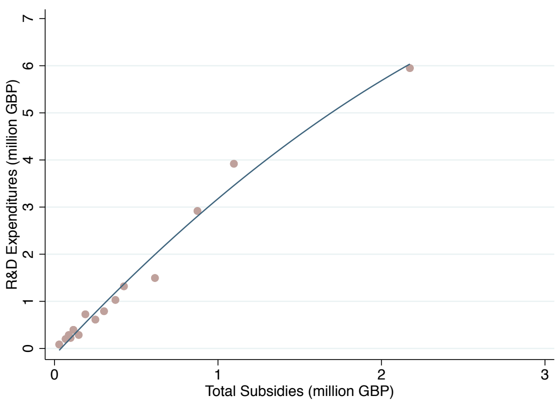
Figure IV: Evidence of No Increasing Returns in Total Subsidies



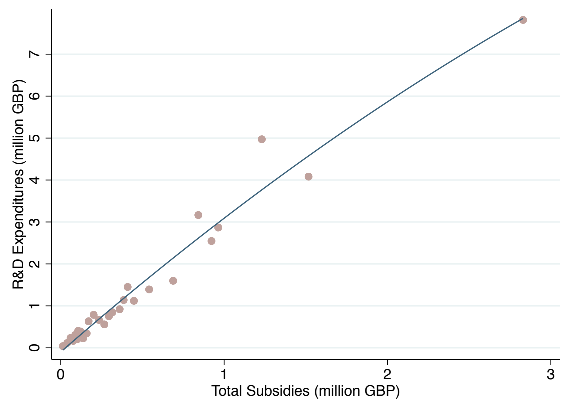
(a) Full Sample, Large Bins



(b) Full Sample, Small Bins



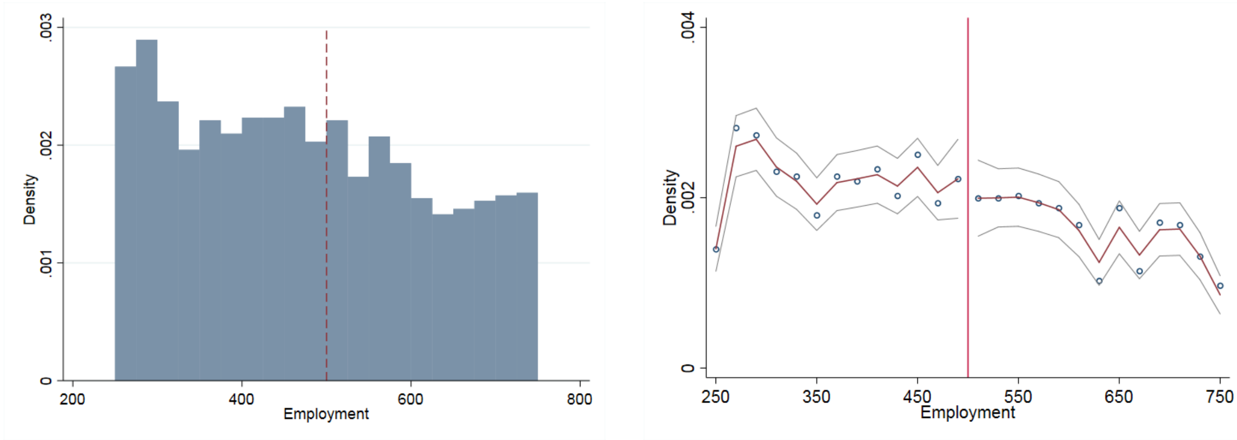
(c) Winsorized Sample, Large Bins



(d) Winsorized Sample, Small Bins

Note: Figures plot R&D expenditures as a function of total subsidies (direct grants and an implied tax credit amount) for small firms. Each point represents the average R&D expenditures for a group of firms. There are 15 bins of firms in Panels A and C and 30 bins of firms in Panels B and D. The full sample of small firms is used in Panels A and B and outliers are dropped in Panels C and D.

Figure V: Evidence of No Manipulation at the Tax Credit Generosity Employment Threshold

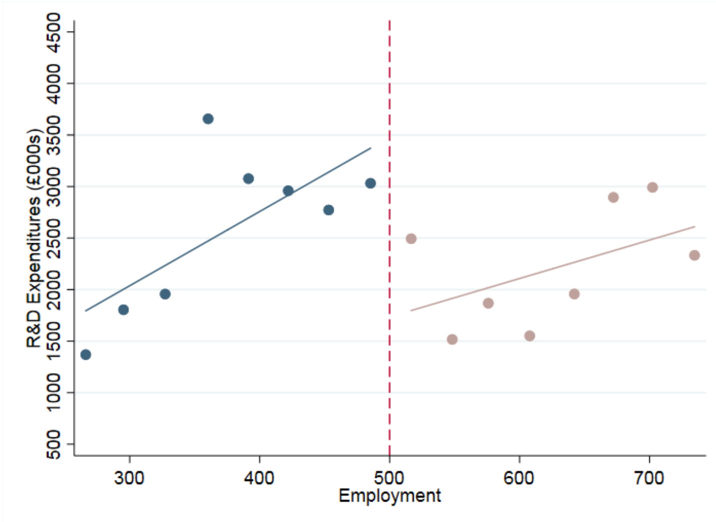


(a) Histogram Based Upon Employment

(b) McCrary Density Test Based Upon Employment

Note: Histogram and McCrary test for discontinuity in distribution density of total employment at the small firm employment threshold. Sample includes firms with fewer than 100 employees. Log difference in density height of -0.1082 with a standard error of 0.3226.

Figure VI: Impact of Tax Credit Policy on R&D Expenditures, Larger Firms



Note: Data points represent average R&D expenditures for evenly-sized bins of firms receiving direct subsidies with 250 to 750 employees. Only data from the post-policy period are included (2009 through 2014). The running variable (employment) is on the x-axis.

A Appendix: Data Preparation – For Online Publication Only

Accessing and linking information on firm-level R&D expenditures and public subsidies is difficult for two reasons. First, most of the required datasets are not publicly available independently. Second, legal promises often restrict matching of the datasets. This Appendix details the data access process and matching procedures applied in order to overcome these barriers, as well as the rules followed for the final data sample preparation.

A.1 Data Preparation for Small Firm Analysis

Direct Grants for R&D.—To identify firms receiving direct grants through Innovate UK, which are either treated or not treated by more generous grant generosity levels determined by the program's rules, I begin with Innovate UK's Transparency Database. This contains grant information since the program's inception, providing details on the grant amount award, total project costs, grant year, and competition title. I keep only data from 2008 through 2017 to drop data on firms leading up to the great recession and to drop 2018 data, which were incomplete at the start of this project. I also drop projects that were withdrawn from the program and thus did not receive grants. Since some firms receive multiple grants from different competitions in each year, I aggregate the data to the firm-year level. The database contains unique company registration numbers (CRNs) so that firms can be uniquely identified.

Firm R&D Expenditures, Employment, and Other Economic Variables.—Firm-level R&D expenditures data are primarily obtained through Burean van Dijk's FAME dataset for the small firm analysis, which provides detailed data on the accounts of incorporated firms in the UK. The dataset covers detailed financial information for 3 million active companies, as well as information on 2.3 million companies that include unincorporated companies that are active but not required to file accounts or have yet to file their first accounts. It also includes 7 million companies that are on longer active. The dataset as a whole contains company balance sheet and income statement data from annual accounts filed at the UK company registry. With the help of the staff at Bureau van Dijk, I was able to build a database of company accounts for the firm's identified as receiving Innovate UK grants from 2008 through 2017. The FAME data also includes information on employment, which is needed for determining grant rate eligibility based upon the Innovate UK funding rules. I convert the financial variables in FAME into real 2010 terms using the World Bank's CPI indicators for each year. FAME also provides other useful information that I use as controls in some specifications, such as industry, location, and birth year.

Calculating Travel Distance and Time.—I find each firm's distance to Innovate UK's London office based upon their postcodes. To do this, I obtained a full list of the UK's postcodes that included their latitudes and longitudes. I take just the outward code plus the first character of the inward code to identify the postcode's neighborhood (due to limitations on the geocoding package that I use) and average the latitudes and longitudes for each modified postcode. I then find the travel distances, measured in kilometers and driving minutes, of each modified postcode to the London headquarters of the UK's funding agency's latitude and longitude.

Matching Innovate UK Data to FAME.—Once aggregating the Innovate UK data to the firm-year level, there are 15,167 observations capturing grants given through Innovate UK. I successfully match 12,540 of these to FAME based on their company registration numbers (CRNs). There are no meaningful differences in those that do not match. Unsuccessful matches are primarily due to incorrectly formatted or missing CRNs. I create variables for the total number of grants each firm receives over the sample period. I then match these data to the travel distance and time calculations.

Additional Outcome Details.—A separate data matching process is required to study the more detailed innovation investment outcomes of small firms, since FAME only provides very basic information about R&D expenditures. I obtained permission from the ONS to import the Innovate UK Transparency Data into the Secure Lab so that the Innovate UK data could be matched with the UK's Community Innovation Survey (CIS) database and the Business Enterprise Research and Development (BERD) database. The UK Innovation Survey has been conducted biannually since 1994 and has served as the main source of information on business innovation in the UK. Like the other innovation surveys conducted throughout Europe, guidelines provided by the OECD's Oslo Manual are followed regarding statistical procedures and definitions of innovation concepts. The surveys contain Inter-Departmental Business Register (IDBR) reference numbers that anonymously but uniquely identify firms in the UK so the data can be linked to other microbusiness datasets. Businesses with 10 or more employees are sampled in a one-stage stratified random sample with up to about 16,000 enterprises per year. Generally, the survey covers questions related to innovation activity, innovation outcomes, context for innovation, and more general economic information. The BERD data are described in the large firm data description.

Although the Innovate UK data also contain unique company reference numbers, these are not the same as those used by the UK Data Services in the Secure Lab, which are anonymized. As such, UK Data Services replaced the CRNs with anonymous enterprise numbers so that they could be matched to other datasets within the Secure Lab. This resulted in an excellent match rate and retaining about 80 percent of the Innovate UK data with new unique firm identifiers. I prepare the Innovate UK data in the same way as before.

The CIS is conducted only biannually, whereas the Innovate UK data is collected annually. I aggregate the Innovate UK data to the biannual level. Ultimately this only matters for tracking which firms receive a grant within each two-year period. The CIS data limits the data only through 2014, so the final Innovate UK data is aggregated to the biannual level from 2008 through 2014. This includes 6,830 observations. The data are fairly unbalanced across years, however. There are about 3k observations for the year 2014, whereas there are only about 1k observations for 2008 and 2010 and 2k observations for 2012. Upon matching the data with CIS, the final dataset contains only 372 observations, but observables are still balanced around the small firm threshold and there is no evidence of bunching for this sample of firms.

A.2 Data Preparation for Larger Firm Analysis

UK Data Services Secure Lab.—The regression analysis for large firms entails linking several microbusiness datasets that are legally protected and held by the UK's Office of National Statistics (ONS). Accessing the data requires a special procedure, which begins with training and taking an exam regarding the use and protection of sensitive data to become a UK Accredited Researcher. A research proposal then must be submitted and approved, justifying the use of the datasets and providing the reasons that they must be accessed and linked in order to answer a question that is relevant for the UK's public good. Once approved, all data use and analysis must be conducted in the UK Data Services Secure Lab environment.

Firm R&D Expenditures.—The primary dataset I use to examine firm-level R&D expenditures is the Business Enterprise Research and Development (BERD) survey. The BERD survey is conducted by the ONS following the Frascati Manual methodology (OECD 2002). It collects data on R&D expenditures and other characteristics of firms identified as actively performing R&D. A stratified sampling approach is employed to select which enterprises will receive a BERD questionnaire. The ONS primarily uses the Annual Business Survey (ABS) to identify R&D-performing firms as well some other data sources such as the UK Community Innovation Survey and HMRC data on firms claiming R&D tax credits.

I start by collecting BERD data from 2000 through 2014 and omit defense-related R&D investments, as these represent a different type of innovation process and such projects likely receive government support in ways that systematically differ from civil-related R&D projects. All questionnaire forms sent to those identified in the stratified sampling include a minimum set of questions on total R&D spending and R&D employment. The largest spenders on R&D receive "long form" questionnaires and the remainder receive a "short form". The short form asks for basic information related to R&D, such as in-house and extramural expenditures and total headcount of R&D employees. The long form covers more detailed information, such as how R&D expenditures are spent based upon capital and non-capital expenditures. Enterprises not included in the stratified sampling, and responses to questions on the long form from firms that were just sent a short form, have imputed values. These are the mean values of the variable as a share of employment in the firm's size band-sector group.

The full BERD datasets begin with about 30,000 observations per year. I take a number of steps to prepare the data for analysis. First, I do not use imputed values in order to avoid introducing measurement. Omitting observations with imputed responses for the key outcome variable of interest (R&D expenditures) reduces the sample size significantly, leaving about 2,500 observations per year. Next, I omit observations where the IDBR reporting unit number seems as though it was recorded incorrectly due to taking on the wrong format. I also drop observations where the IDBR is duplicated, as there is no consistent way of understanding which entry is correct when the responses do not align. In total, this results in dropping only a very small number of observations (<0.01 percent).

Finally, the BERD responses are observed at the IDBR reporting-unit level, but funding and tax credit eligibility rules are determined by firm characteristics at the "enterprise group" level, which is a larger statistical unit. The EU Regulation on Statistical Units defines enterprise groups as "an association of enterprises bound together by legal and/or financial links" (EEC 696/93). The reporting unit level is associated with a geographical unit, whereas enterprise groups capture all reporting units associated with an enterprise.

The BERD datasets for each year include all reporting unit-year observations that were identified by ONS as firms performing R&D in the UK, yet the assignment to treatment in this analysis depends on whether the enterprise group satisfies the eligibility criteria. I aggregate the BERD data to the enterprise group level so that it can be matched to the Business Structure Database (BSD), which provides data on the enterprise group's total employment, and so that the R&D expenditure data captures the entire enterprise group's R&D investment levels. Furthermore, the location where R&D funds are allocated to an enterprise might not be the same local-level reporting level that is observed in BERD.

This aggregation process results in only a very small further reduction in the sample size. For instance, for the year 2014, this results in a sample size of 2,497 observations from 2,544 observations. The most restrictive aspect of the data preparation for the sample size is the use of only non-imputed data. The final step is matching firms in BERD over time from 2000 to 2014. The final BERD dataset used in this analysis prior to matching to other datasets consist of about 2,000 to 2,500 enterprise groups per year.

Determining Funding Level Eligibility.—I use the UK's Business Structure Database (BSD) to determine each enterprise group's tax credit rate eligibility. The BSD is also held securely by the ONS and requires UK Data Services Secure Lab access. It includes information on a small set of variables for nearly all businesses in the UK, and since it allows for one to observe a reporting unit's enterprise group, I use this to determine each enterprise group's employment level and thus tax credit rate eligibility. The data are derived mostly from the Inter-Departmental Business Registrar (IDBR), which is a live register of administrative data collected by HM Revenue and Customs including all businesses that are liable for VAT and/or has at least one member of staff registered for the Pay As You Earn (PAYE) tax collection system. The BSD only misses very small businesses, such as those that are self-employed, and covers almost 99 percent of the UK's economic activity.

The BSD annual datasets include variables such as local unit-level and enterprise-level employment, turnover, company start-up date, postcodes, and the Standard Industrial Classification (SIC). I aggregate variables to the enterprise group level. If the observation is missing an enterprise number and does not belong to a larger enterprise group, I use the given observation's values for each variable. There are about 3 million observations per year. The enterprise group numbers are anonymous but unique so that they can be linked to other datasets held by the ONS.

Travel Distance and Time.—I follow the same procedures for finding firms' distances from the main innovation funding agency in London as described in Appendix A1.

Linking Datasets.—I begin by matching the BERD data to the full list of firms' postcodes from the BSD. This provides an almost-fully populated list of postcodes in the BERD sample data, however, if the postcode is missing, I use the postcode provided in BERD (only 26 observations). I match these data to the travel distance and time data using just the outward code and first character of the inward code of the postcodes. Merging this to the distance data results in an excellent match—less than 0.1 percent of the BERD data do not match. For those that do not match, I interpolate the missing values with the average values of the distance variables within postal areas (the first two characters of the firm's postcode). Finally, I merge the BERD and distance dataset to the BSD at the enterprise group-year level, which results in 99.9 percent of the sample matching with the BSD.

Final Data Sample Preparation.—A few final steps are taken to prepare the data for analysis. First, all expenditure and financial variables are converted into real 2010 terms using the World Bank's Consumer Price Index. Observations associated with inactive firms are dropped from the sample, which results in dropping only 72 observations. I omit outliers based upon a 1% winsorization rule based upon the R&D expenditure distribution in the years from 2008 through 2014. The final subsample of the data used includes about 2,000 to 2,500 firms per year from 2000 through 2014.

B Appendix: Additional Tables – For Online Publication Only

Table B.1: No Discontinuity in Covariates at Threshold, Small Firms

	Total Assets	Current Liabilities	Cost of Sales	Credit Limit	Total Cost of Proposed Project	No. of Grants
	(1)	(2)	(3)	(4)	(5)	(6)
1[employment < 50]	8.94	5.71	163.8	0.50	700.79	-0.370
	(10.27)	(8.22)	(160.91)	(0.32)	(22.44(	(0.33)
Employment * 1[employment < 50]	-0.15	0.14	3.3	0.00	22.44	0.02*
	(0.45)	(0.29)	(3.82)	(0.01)	(36.37)	(0.01)
No. of Observations	1,166	1,158	816	1,059	1,157	1,168

Notes: Dependent variables are other covariates where discontinuities are not expected. Total assets, current liabilities, cost of sales, and credit limit are in millions (GB) and total cost of proposed project is in thousads. Number of grants is the number of grants received by each firm over the years 2008 through 2017. Firms with less than 100 employees receiving grants are included. First order polynomials of the (centered) running variable (employment) are included separately for each side of the threshold. Standard errors are clustered by industry. Asterisks denote *p <0.10, **p <0.05, ***p <0.01.

Table B.2: Sample of UK Policies Providing Benefits for Smaller Firms

Policy/Program	Description	Firms Affected
Small Business Rate Relief	Relief from property business rates charged on non-domestic properties like shops, offices, and factories.	Firms with rateable value less than £15k or business uses only one property.
Corporate Taxes	There is a single Corporation Tax rate of 20% for non-ring fence profits.	Determined by profits as opposed to turnover, employment, or total assets.
Employment Allowance	Discount on National Insurance bill.	Any business paying employers' Class 1 National Insurance
Venture Capital Schemes: Enterprise Investment Scheme, Seed Enterprise Investment Scheme, and Social Investment Tax Relief	Tax relief provided to investors of venture capital schemes. Depending on the scheme, relief is provided against income tax or capital gains tax.	Tax relief is provided to investors as opposed to firms.
Enterprise Investment Scheme	A venture capital scheme that helps companies raise money.	Firms must not have gross assets worth more than £15m before shares are issued (and £16m afterwards), and must have fewer than 250 employees.
Seed Enterprise Investment Scheme	A venture capital scheme that helps companies raise money.	Firms must not have gross assets worth more than £200k at the time when shares are issued, and must have fewer than 25 employees.
Small Business: GREAT Ambition	A commitment to helping small businesses grow, providing feedback to small businesses about how government can help in hiring, breaking into new markets, etc.	No firm size definitions that align with the Innovate UK definitions.
British Business Bank	A business development bank committed to making finance markets work better for small businesses.	Support programs for start-ups and small businesses in general with no noticeable advantages to firms that align with the firm size definitions for grant generosity.
Employer NI Contributions	Employers pay secondary national insurance contributions to HMRC.	Rates are determined by profits as opposed to employment, turnover, or total assets.
Value Added Tax	VAT registration is required for firms of a certain size.	The threshold for VAT registration is £85k.
Pay As You Earn	Payment by employers as part of the payroll so that the HMRC can collect income tax and national insurance.	Income tax rates depend on how much of taxable income is above personal allowance, and rates are determined by earnings.
Export Credits Guarantee Scheme	Encourages exports by SMEs by ensuring successful implementation of scheme.	Applies to all SMEs, not just small firms.
Loan Guarantees for SMEs	Government agreement with large banks to extend loans to small businesses in the UK, increasing the availability of finance.	Applies to all SMEs, not just small firms.
Enterprise Capital Funds	Financial schemes to address the provision of equity finance to certain firms and to invest in high growth businesses.	Applies to all SMEs, not just small firms.
Business Angel Co-Investment Fund	A £100M investment fund for UK businesses.	Applies to all SMEs, not just small firms.

Notes: Table provides information on a sample of other policies in the UK that provide incentives for small businesses. No policies that could confound the diff-in-disc estiamtes for small firms are found.

Table B.3: No Difference in the Discontinuity in Covariates at Threshold, Small Firms

	Total Assets	Current Liabilities	Cost of Sales	Credit Limit	Total Cost of Proposed Project	No. of Grants
	(1)	(2)	(3)	(4)	(5)	(6)
1[year = post 2012] *1[employment < 50]	-40.27	-13.51	-148.02	-0.29	1393.92	-0.08
	(26.57)	(11.43)	(151.51)	(0.39)	(1303.98)	(0.12)
1[year = post 2012] *1[employment < 50] *employment	-0.13	-0.28	-3.35	0.00	39.67	0.01
	(0.89)	(0.30)	(3.14)	(0.01)	(52.24)	(0.00)
1[employment < 50]	35.6	14.46	148.17	0.34	-215.63	-0.06
	(26.02)	(13.84)	(150.83)	(0.31)	(208.21)	(0.12)
No. of Observations	1,166	6,759	4,816	6,230	1,145	6,809

Notes: Dependent variables are other covariates where differences in discontinuities are not expected. Total assets, current liabilities, cost of sales, and credit limit are in millions (GB) and total cost of proposed project is in thousads. Number of grants is the number of grants received by each firm over the years 2008 through 2017. Firms receiving grants and with less than 100 employees are included. First order polynomials of the (centered) running variable (employment) are included separately for each side of the threshold. Standard errors are clustered by industry. Asterisks denote *p <0.10, **p <0.05, ***p <0.01.

Table B.4: Robustness of Tax Credit Change Timing, Small Firms

	Wide Window (< 100 Empl.)	Midrange Window (10 to 90 Empl.)	Narrow Window (20 to 80 Empl.)
	(1)	(2)	(3)
Panel A: Pseudo Tax Credit Change in 2013			
1[year = post 2013] *1[employment < 50]	1927.69	1858.8	600.21
	(1581.46)	(1740.94)	(1757.91)
1[year = post 2013] *1[employment < 50] *employment	9.8	95.01	94.35
	(30.66)	(77.73)	(84.06)
Panel B: Pseudo Tax Credit Change in 2014			
1[year = post 2014] *1[employment < 50]	2687.53	2237.55	1123.98
	(2290.83)	(2350.49)	(2491.65)
1[year = post 2014] *1[employment < 50] *employment	-8.14	63.52	91.46
	(32.76)	(74.17)	(91.45)
Sample mean for dependent variable	£1,302	£1,433	£1,478
No. of Observations	196	155	124

Notes: Falsification tests regarding the year of the tax credit rate change. Firms receiving grants and with fewer than 100 employees are included. Standard errors are clustered by industry. Asterisks denote *p <0.10, **p <0.05, ***p <0.01.

Table B.5: Additional Robustness Checks for R&D Expenditures Results, Small Firms

	Triangular Weights, Wide Window (1)	Triangular Weights, Narrow Window (2)	Quadratic Polynomials (3)	Cubic Polynomials (4)	Dropping Fewer Outliers (5)
1[year = post 2012] *1[employment < 50]	2346.71*	2478.57*	2266.89**	2085.74**	2143.32*
	(1150.95)	(1383.46)	(851.16)	(896.23)	(1188.73)
1[year = post 2012] *1[employment < 50] *employment	66.87	84.35	37.85	47.35	19.63
	(46.55)	(69.55)	(36.73)	(40.24)	(25.12)
1[employment < 50]	-1058.63	-769.45	-916.87	-1103.21	-1120.26
	(743.31)	(768.84)	(1017.86)	(1437.40)	(877.82)
Sample mean for dep. variable	£1,423	£1,474	£1,302	£1,302	£1,168
No. of Observations	196	124	196	196	219

Notes: Dependent variable is total R&D expenditures (£000s). Columns 1-2 use triangular weights rather than uniform. Columns 3-4 use higher order polynomials of the running variable. Column 5 winsorizes at the 1% level rather than 5%. All controls are the same as in the baseline regressions. Firms with fewer than 100 employees are included. Standard errors are clustered by industry. Asterisks denote *p <0.10, **p <0.05, ***p <0.01.

Table B.6: Types of Innovation Efforts and Outcomes, Small Firms

Dependent Variable:	To Enter New Market (1)	To Improve Goods Quality (2)	Goods Innovation (3)	Process Innovation (4)
Panel A: Wide Window (<150 Employees)				
1[year = post 2012] * 1[employment <50]	1.36**	-1.06**	0.71**	0.15
	(0.57)	(0.42)	(0.26)	(0.26)
No. of Observations	137	139	187	181
Panel B: Midrange Window (<120 Employees)				
1[year = post 2012] * 1[employment <50]	1.51**	-1.25***	0.87**	0.03
	(0.68)	(0.43)	(0.28)	(0.29)
No. of Observations	127	129	173	169
Panel C: Narrow Window (10 to 90 Employees)				
1[year = post 2012] * 1[employment <50]	2.12**	-1.46***	0.91***	0.13
	(0.95)	(0.44)	(0.26)	(0.27)
No. of Observations	113	114	153	151

Notes: Dependent variables capture whether firms report making different types of innovation efforts or achieving different outcomes (from the CIS dataset). In Columns 1 and 2, the dependent variables measure how important entering a new market versus improving quality of goods or services is in the decision to innovate, respectively, rated on a scale from 0 (low importance) to 4 (high importance). In Columns 3 and 4, the dependent variables are indicators for whether the firm reports introducing new or significantly improved goods or a process for producing goods and services, respectively. First order polynomials of the (centered) running variable (employment) are included separately for each side of the threshold. Specifications also include dummies for size threshold, size threshold by centered employment, treatment year (equal to one if the year is post-2012), and treatment year by centered employment. Standard errors are clustered by industry. Asterisks denote *p <0.10, **p <0.05, ***p <0.01.

Table B.7: Direct Subsidy and Outcome Descriptive Statistics, Larger Firms

	Wide Window (150 to 850 Employees) (1)	Midrange Window (250 to 750 Employees) (2)	Narrow Window (350 to 650 Employees) (3)
R&D Expenditures (£000s)	£1,293	£1,357	£1,366
	(£2,647)	(£2,732)	(£2,839)
Direct Subsidy Amount (£000s)	£81	£77	£87
	(£431)	(£369)	(£432)
Proportion of R&D Expenditures Funded (%)	5.5%	5.5%	5.6%
	(9.1%)	(9.2%)	(9.4%)
No. of Observations	2,699	1,754	1,051

Notes: Descriptive statistics of subsidy and outcome variables for sub-samples of varying window sizes around the R&D tax credit generosity threshold. Standard deviations in parentheses. Data include years 2009 through 2014 for firms receiving direct subsidies.

Table B.8: Corroborating Small Firm Results with Alternative Data

	Wide Window (< 150 Empl.) (1)	Midrange Window (120 Empl.) (2)	Narrow Window (10 to 90 Empl.) (3)
Panel A: Effects on Total R&D Expenditures			
1[year = post 2012] *1[employment < 50]	3611.94**	4233.63**	4064.27
	(1297.40)	(1805.51)	(2490.17)
Sample mean for dependent variable	$£1,321$	$£1,217$	$£1,727$
No. of Observations	262	247	149

	Internal Finance (1)	External Finance (2)
Panel B: Effects on Privately-Financed R&D		
1[year = post 2012] *1[employment < 50]	4274.08***	-25.08
	(1455.13)	(41.05)
Sample mean for dependent variable	$£1,089$	$£61$
No. of Observations	262	262

Notes: In Panel A, Dependent variable is total R&D expenditures. The first row of each column provides the difference-in-discontinuities estimate. Results are for sub-samples of data around the grant generosity threshold for small firms. In Panel B, dependent variables are proxies for internal and external private finance for R&D. In Column 1 of Panel B, internal financing of R&D is the firm's expenditures on performing R&D funded by the firm's own funds as well as other overseas organizations, including subsidiaries or the parent company. In Column 2 of Panel B, external private finance is the firm's expenditures on performing R&D funded by private businesses in the UK and other organizations besides the government, such as private non-profits. In all specifications, first order polynomials of the (centered) running variable (employment) are included separately for each side of the threshold. Specifications also include dummies for size threshold, size threshold by centered employment, treatment year (equal to one if the year is post-2012), and treatment year by centered employment. Other controls include firm age, distance to London, total grant funding awarded to the firm's competition, total grant funding awarded in the year, and year fixed effects. Standard errors are clustered by industry. Asterisks denote *p <0.10, **p <0.05, ***p <0.01.

Table B.9: Falsification Tests for Diff-in-Disc Using Alternative Data, Small Firms

	Wide Window (1)	Midrange Window (2)	Narrow Window (3)
Panel A: 30 Employee Pseudo-Threshold			
1[year = post 2012] *1[employment < 30]	563.93	-328.95	-386.67
	(1041.43)	(822.88)	(1138.03)
Sample mean for dependent variable	£1,217	£1,194	£1,047
No. of Observations	247	239	224
Panel B: 70 Employee Pseudo Threshold			
1[year = post 2012] *1[employment < 70]	-1314.22	-1494.82	-2313.91
	(1562.89)	(1225.47)	(2008.55)
Sample mean for dependent variable	£1,332	£1,321	£1,777
No. of Observations	272	262	169

Notes: Dependent variable is total R&D expenditures. Results provide falsification tests of the difference-in-discontinuities estimates for small firms, imposing artificial thresholds for grant generosity, and estimating separate regressions for sub-samples of data around these pseudo-thresholds. The wide, midrange, and narrow windows in Panel A include firms with less than 120, 100, and 80 employees, respectively. In Panel B, they include firms with less than 170, less than 150, and between 10 and 130 employees, respectively. First order polynomials of the (centered) running variable (employment) are included separately for each side of the threshold. Specifications also include dummies for size threshold, size threshold by centered employment, treatment year (equal to one if the year is post-2012), and treatment year by centered employment. Other controls include firm age, distance to London, total grant funding awarded to the firm's competition, total grant funding awarded in the year, and year fixed effects. Standard errors are clustered by industry. Asterisks denote *p <0.10, **p <0.05, ***p <0.01.

Table B.10: Tax Credit Policy Effects Only, Larger Firms

	Linear Polynomial Controls			Quadratic Polynomial Controls		
	Wide Window (1)	Midrange Window (2)	Narrow Window (3)	Wide Window (4)	Midrange Window (5)	Narrow Window (6)
Panel A: Post-Policy Period						
1[employment < 500]	1533.34*	1631.45*	1738.14**	1199.70*	922.98*	459.53
	(767.51)	(814.06)	(752.44)	(643.44)	(524.30)	(524.13)
Sample mean for dep. var.	£2,395	£2,412	£2,415	£2,395	£2,412	£2,415
No. of Observations	2,613	2,348	2,121	2,613	2,348	2,121
Panel B: Pre-Policy Period						
1[employment < 500]	576.95	559.54	630.7	413.05	433.23	217.76
	(373.32)	(398.36)	(442.05)	(650.84)	(654.88)	(644.40)
Sample mean for dep. var.	£1,927	£1,930	£1,955	£1,927	£1,930	£1,955
No. of Observations	3,451	3,084	2,764	3,451	3,084	2,764

Notes: Dependent variable is total R&D expenditures. The first row of each column in Panel A reports the estimated local average treatment effect of receiving more generous tax credits (determined by the 500 employee threshold in the post-policy period) for varying sub-samples of data around the threshold. The first row of each column in Panel B reports the estimated local average treatment effect in pre-policy years, confirming that no discontinuity was present before the tax credit generosity employee threshold was changed. First (Columns 1-3) and second (Columns 4-6) order polynomials of the (centered) running variable (employment) are included separately for each side of the threshold. Standard errors are clustered by industry. Asterisks denote *p <0.10, **p <0.05, ***p <0.01.

Table B.11: Effects on Types of R&D Expenditures, Larger Firms

	Basic Research Expenditures		Applied Research Expenditures		Experimental Dev. Expenditures	
	(1)	(2)	(3)	(4)	(5)	(6)
	<500	≥ 500	<500	≥ 500	<500	≥ 500
Direct Subsidies (£000s)	0.783***	0.175**	1.430***	4.799***	1.009*	1.882**
	(0.069)	(0.071)	(0.148)	(1.394)	(0.516)	(0.835)
No. of Observations	848	635	848	635	848	635
Difference at Threshold	0.608***		-3.369**		-0.873	
	(0.099)		(1.402)		(0.982)	

Notes: Dependent variables are the firm's expenditures on basic, applied, and experimental development R&D. The first row of each column reports the estimated average effect of direct subsidies below and above the tax credit generosity threshold for firms with 250 to 750 employees. All specifications include controls for employment, age, distance to funding agency HQ, total value of subsidies allocated to each industry-year, and fixed effects for year, business structure, product group, and industry. Standard errors are clustered by industry. Asterisks denote *p <0.10, **p <0.05, ***p <0.01.

Table B.12: Sensitivity of Estimates to Employment Polynomial Flexibility, Larger Firms

	Linear		Quadratic		Cubic	
	(1)	(2)	(3)	(4)	(5)	(6)
	<500	≥ 500	<500	≥ 500	<500	≥ 500
Direct Subsidies (£000s)	3.229***	6.610***	3.229***	6.606***	3.229***	6.642***
	(0.607)	(1.366)	(0.607)	(1.371)	(0.603)	(1.368)
No. of Observations	848	635	848	635	848	635
Difference at Threshold	-3.381**		-3.377**		-3.413**	
	(1.495)		(1.499)		(1.495)	
Linear employment trend (baseline)	x	x				
Quadratic employment trend			x	x		
Cubic employment trend					x	x

Notes: Dependent variable is total R&D expenditures. Estimates report the average effect of direct subsidies from separate OLS regressions below and above the tax credit generosity threshold with increasing flexibility of the employment variable control. Firms with 250 to 750 employees are included. All specifications also include controls for employment, age, distance to funding agency HQ, total value of subsidies allocated to each industry-year, and fixed effects for year, business structure, product group, and industry. Standard errors are clustered by industry. Asterisks denote *p <0.10, **p <0.05, ***p <0.01.

Table B.13: First Stage Results for IV Regressions, Larger Firms

	Primary IV Approach		Alternative IV #1		Alternative IV #2	
	(1)	(2)	(3)	(4)	(5)	(6)
	<500	≥ 500	<500	≥ 500	<500	≥ 500
Instrumental Variable (£000s)	-16.754***	-11.140***	-25.374***	-14.899***	-15.301***	-8.138***
	(3.054)	(2.069)	(5.167)	(3.132)	(4.848)	(2.617)
F-statistic for excluded instrument	30.10	28.99	24.12	22.62	9.96	9.67
No. of Observations	848	635	848	635	848	635
Difference at Threshold	-5.614		-10.475*		-7.163	
	(3.689)		(6.042)		(5.509)	
IV = Travel distance*Total SIC subsidies	x	x				
IV = Time to travel*Total SIC subsidies			x	x		
IV = Travel distance*2-digit SIC subsidies					x	x

Notes: First stage results from IV regression results presented in Table XXX. Dependent variable is direct subsidies for R&D (£000s). The first row of each column reports the estimated average effect of the excluded instrument. The second row reports the F-statistic for the excluded instrument from this first stage. The excluded instrument in Columns 1 & 2 is the interaction of (i) the firm's driving distance in kilometers to the UK's primary funding agency HQ and (ii) the total value of subsidies allocated to the firm's industry-year. The IV in Columns 3 & 4 uses travel distance in time (minutes) rather than distance. The IV in Columns 5 & 6 measures the firm's industry-year subsidies by the first two-digits of the SIC rather than full SIC. All specifications include the main effects interacted in the IV. All specifications also include controls for employment, age, and fixed effects for year, business structure, product group, and industry. Standard errors are clustered by industry. Asterisks denote *p <0.10, **p <0.05, ***p <0.01.

Table B.14: Effects on R&D vs. Non-R&D Employment, Small Firms

Dependent Variable:	R&D Employment (1)	Non-R&D Employment (2)
1[year = post 2012] *1[employment < 50]	31.86***	-3.00
	(14.66)	(20.98)
Sample mean for dep. variable	15	17
No. of Observations	262	262

Notes: Dependent variables are R&D employment (Column 1) and non-R&D employment (Column 2). Results demonstrate that increases in R&D employment are not offset by decreases in non-R&D employment. First order polynomials of the (centered) running variable (employment) are included separately for each side of the threshold. Specifications also include dummies for size threshold, size threshold by centered employment, treatment year (equal to one if the year is post-2012), and treatment year by centered employment. Standard errors are clustered by industry. Asterisks denote *p <0.10, **p <0.05, ***p <0.01.

Table B.15: Persistence of Substitution Effect Over Time, Larger Firms

Data Sub-Sample:	Post-2010 Only		Post-2012 Only	
	(1)	(2)	(3)	(4)
	<500	≥500	<500	≥500
Direct Subsidies (£000s)	2.281***	6.264***	2.273***	5.672**
	(0.264)	(1.472)	(0.232)	(2.448)
No. of Observations	553	432	373	314
Difference at Threshold	-3.983***		-3.399	
	(1.495)		(2.459)	

Notes: Dependent variable is total R&D expenditures. Columns 1 and 2 include observations only after 2010, and Columns 3 and 4 include observations only after 2012. The first row of each column reports the estimated average effect of direct subsidies from separate regressions below and above the tax credit generosity threshold for firms with 250 to 750 employees. All specifications include controls for employment, age, distance to funding agency HQ, total value of subsidies allocated to each industry-year, and fixed effects for year, business structure, product group, and industry. Standard errors are clustered by industry. Asterisks denote *p <0.10, **p <0.05, ***p <0.01.

Table B.16: Effects on Capital vs. Non-Capital R&D Expenditures, Larger Firms

Dependent Variable:	Capital R&D Expenditures		Non-Capital R&D Expenditures	
	(1)	(2)	(3)	(4)
	<500	≥500	<500	≥500
Direct Subsidies (£000s)	0.137***	0.155	3.092***	6.455***
	(0.026)	(0.177)	(0.581)	(1.221)
No. of Observations	848	635	848	635
Difference at Threshold	-0.018		-3.363**	
	(0.179)		(1.352)	

Notes: Dependent variables are capital (Columns 1-2) and non-capital (Columns 3-4) expenditures on R&D. Capital expenditures are on land and buildings as well as equipment and machinery. Non-capital expenditures are mostly salaries for R&D workers. The first row of each column reports the estimated average effect of direct subsidies below and above the tax credit generosity threshold for firms with 250 to 750 employees. All specifications include controls for employment, age, distance to funding agency HQ, total value of subsidies allocated to each industry-year, and fixed effects for year, business structure, product group, and industry. Standard errors are clustered by industry. Asterisks denote *p <0.10, **p <0.05, ***p <0.01.