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

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Abstract

Governments often subsidize private R&D using both direct subsidies and tax incentives. In this paper, I develop a framework for studying their interdependence, which also provides a test for detecting capital market imperfections. I implement two quasi-experimental research designs to examine firms in the United Kingdom and show that grants and tax credits are complements for small firms but substitutes for larger firms. Higher tax credit rates substantially enhance the effect of grants on R&D investment for small firms, particularly those facing financial constraints, but they reduce it for larger firms. The productivity of small firms also increases. My findings imply that the innovation policy mix should include both support mechanisms for small firms only.

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

JEL codes: D22, H0, H25, L53, O31, O32, O38

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1 Introduction

Fostering innovation is one of the longest-standing and most pressing economic challenges. In an effort to stimulate innovative activity, governments globally provide subsidies for private research and development (R&D), comprising hundreds of billions of dollars in public expenditures each year. Subsidies come in various forms—most commonly direct grants and tax incentives—and the economic case for such intervention is clear. Firms do not fully appropriate the benefits of their investments and thus competitive markets tend to under-supply innovation (Nelson 1959; Arrow 1962). There is growing evidence that various types of subsidies have positive effects on innovative activity. For example, Howell (2017) and Azoulay, Graff Zivin, Li and Sampat (2018) find that direct grants have positive impacts on patenting, and Bøler, Moxnes and Ulltveit-Moe (2015), Guceri and Liu (2019), and Agrawal, Rosell and Simcoe (2020) find that tax incentives increase R&D. However, if the two mechanisms are not independent, accounting for their interaction is critical when evaluating their effects and for informing policy design.

In this paper, I develop a framework showing how R&D grants and tax credits can be complements or substitutes, and I implement two quasi-experimental research designs to study their effects on R&D for firms in the United Kingdom. As an example of how such subsidies are intertwined, consider the expenditures that typically qualify for tax credits. In the US and UK, firms cannot claim tax credits on grant-funded R&D. Grants thus mechanically reduce tax credits, implying that the two support mechanisms are substitutes. On the other hand, firms may face financing constraints and require upfront support to overcome high start-up costs, such as those related to purchasing new machinery. Tax credits can then enable firms to hire more scientists to use the machinery. This increases R&D expenditures associated with the grant-funded capital and implies that the two subsidies are complements. The model I develop shows that they can only be complements if firms face financing constraints, and thus it also provides a direct test for detecting capital market imperfections.

My empirical setting offers the rare opportunity to study the interaction of grants and tax credits in ways that allow for a causal interpretation of the interaction. I use different sources of policy-induced variation in the cost of investing in R&D, and I implement two empirical strategies to study both small and large firms. Sensitivities to cash flow shocks and innovation incentives may vary across the firm size distribution, and in the context of innovation, firm size is particularly important because of its implications for productivity and the types of innovations realized.[1]

[1]For example, Akcigit and Kerr (2018) and Akcigit and Serrano-Velarde (2020) show that the types of innovations produced can differ by firm size, and Bloom and van Reenen (2007) and Bloom, Mahajan, McKenzie and Roberts (2013) show that different management practices impact

Accounting for such heterogeneity requires two approaches given the variation that allows for identifying the interaction effects in my setting. For small firms, I take a difference-in-discontinuities approach (henceforth "diff-in-disc") to study grants provided by Innovate UK, the UK's largest public body that funds private R&D. This entails exploiting a sharp discontinuity in firm size that defines funding generosity, whereby different grant award rates (i.e., the proportion of proposed project costs that the funding agency subsidizes when firms win grants) apply for firms below and above a 50 employee threshold. I then use before and after variation to estimate how increases in the tax credit rate impact the marginal effect of grant funding on R&D expenditures and productivity. Grembi, Nannicini and Troiano (2016) show how this research design recovers a causal (local) difference-in-discontinuity effect in a neighborhood around the threshold, even if the effects of the mechanisms on their own are not identified. I provide evidence that the assumptions for identifying the interaction effect hold, such as by showing that firms do not select into specific grant rates by manipulating their size. They also do not manipulate other factors that determine the level of grant funding they receive, like the type of research that they pursue or their proposed project costs.

To study larger firms, I use a different sharp discontinuity that determines the generosity of tax credits, whereby firms under a 500 employee threshold benefit from higher tax credit rates relative to those over it. There are no other policies or support schemes in the UK that generate differential incentives for firms around this threshold. To examine the tax credit policy's interaction with grants, I estimate the effect of grant funding on each side of the tax credit rate threshold, limiting the sample to firms within a narrow window around it, and calculate the difference in grant effects for firms just under versus over it. This serves as a test of complementarity that provides a causal interpretation, since the *difference* in grant effects is driven strictly by the exogenous variation in tax credit rates. Even though the effect of grant funding on its own is not identified, this approach identifies the interaction effect under a certain set of assumptions that I validate.

My results provide strong evidence that the subsidy schemes are complements for small firms but substitutes for larger firms and the effects are economically significant. For small firms, a 39% increase in the tax credit rate enhances the marginal effect of grant funding so much that R&D expenditures more than double. The findings are robust across many different modelling assumptions and falsification tests. Furthermore, since higher tax credits create an incentive for firms to relabel ordinary investments as R&D expenditures, I provide three pieces of evidence to confirm that the positive effects reflect real innovative activity. First, I show that the policies have no effect on ordinary investments at all. Second, I show that firms

productivity.

do not pass through their subsidies to shareholders, which could occur if firms do not actually use them for R&D (Hall and Lerner 2010). Third, I examine the effects on firm productivity and find that both labor and capital productivity increase. There is also no reallocation of the two inputs. Taken together, these findings indicate that the subsidy interaction effect on R&D reflects a real increase in innovative activity that results in improved productivity.[2]

These findings also suggest that small firms face financing constraints. My theoretical framework shows that the marginal effect of grants can only increase with more generous tax credits if capital markets are imperfect, absent expenditure relabelling, which I have ruled out. To corroborate this conclusion, I show that the interaction effects are largest for firms that appear to have binding financial constraints as measured in three ways: 1) high short-term debt, which typically reflects not having sufficient internal resources to cover unexpected costs, 2) before-tax profits, and 3) available funds for investment as measured by the sum of before-tax profits and depreciation (Zetlin-Jones and Shourideh 2017). The subsidy interaction effects are large and positive for firms that are constrained according to all three proxies but insignificant for those that are not.

The results are entirely flipped for larger firms. Tax credit rates are, on average, 17 percentage points higher for firms under the tax credit generosity threshold relative to those over it. By estimating the difference in grant effects around the threshold, I find that higher tax credit rates *dampen* the effect of direct grants for larger firms. The impact is substantial: the effect of grant funding is cut in half. To provide further confidence that the dampening effect is driven by the tax credit policy, I also show that the effects occur for non-capital R&D expenditures, which account for the majority of R&D qualifying for tax credits in the UK, but not capital R&D expenditures, which do not qualify. The negative, large, and statistically significant difference in the marginal effect of grant funding indicates that the two subsidies are substitutes and that these firms are unconstrained. Larger firms thus must be already investing in all profitable opportunities, and additional government support leads to the subsidization of infra-marginal expenditures (i.e., expenditures that would have been privately profitable even without additional subsidies).

These findings are important for policy. Innovation has long been recognized as a central driver of economic growth and productivity (Romer 1990; Aghion and Howitt 1992; Jones 1995; Aghion and Howitt 1998; Segerstrom 2000; Klette and Kortum 2004; Syverson 2011), but understanding how to stimulate innovation with policy remains a challenge that is particularly urgent amidst the productivity slowdown experienced by most of the developed world since the mid-2000s (Syverson

[2]One may wonder whether the results reflect increasing returns to total subsidies rather than an interaction effect. I show in Section 2 that this can only occur if the subsidies are complements in the first place.

2016).[3] Direct grants and tax credits are two of the most popular instruments that governments use to subsidize R&D. While there is growing evidence that they have positive effects on innovation when studied on their own, the novel insight from this paper is that such mechanisms are not always independent in their effects on firm behavior, and thus accounting for the ways in which they interact is critical when evaluating their effects and designing efficient policy. My findings imply that the innovation policy mix should include both support mechanisms for small firms but just one of them for larger firms, or else public funding subsidizes infra-marginal expenditures.

Lastly, 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.[4]

The remainder of this paper is organized as follows. Section 2 develops the theoretical framework and Section 3 describes the institutional setting. Section 4 details the empirical strategies and data, Sections 5 and 6 provide the results, and Section 7 explores the underlying mechanism. The paper concludes in Section 8.

2 Theoretical Framework

Understanding whether policymakers should provide both R&D direct grants and tax credits requires knowing whether they are complements or substitutes. In this section, I develop a theoretical framework for studying subsidy complementarity, which also provides a direct test of capital market imperfections.

I begin by modeling subsidy interdependence within the Hall-Jorgenson cost of capital framework (Hall and Jorgenson 1967; King 1974), treating investment in R&D analogously to investment in physical capital. The model incorporates elements of the common approach to examining R&D tax credits (Hall and Van Reenen 2000; Bloom, Griffith and van Reenen 2002; Guceri and Liu 2019; Agrawal et al. 2020) and the effects of direct grants on firms' capital investments (Criscuolo, Martin, Overman and Van Reenen 2019).

Consider firm i receiving direct grants and tax credits for R&D, choosing its R&D expenditure conditional on both subsidy types to maximize profits, π_i:

$$\pi_i = pf(I_i) - C(I_i(\omega, \eta)), \tag{1}$$

[3] There could be substantial welfare gains from innovation subsidies to firms' investments in innovation (Atkeson and Burstein 2019).

[4] 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).

where p is the price of output, $f(I_i)$ is how R&D investment I_i is transformed into output, and $C(I_i(\omega, \eta))$ is the cost of investing in R&D at level I_i, which is dependent upon the present discounted values of grant funding (ω) and the level of tax credit support (η). Since ω and η do not affect the productivity of R&D spending, understanding whether the two subsidy types are complements or substitutes requires knowing whether firm costs are super- or sub-modular in ω and η.

I introduce subsidy interdependence by allowing tax credits to be a function of grants, such that $\eta = \eta(\omega)$, and let $\eta(\omega)$ be continuously differentiable.[5] This realistically captures how the two mechanisms often work in practice. For instance, in the US and UK, a boost in grant generosity reduces the amount of funding received through tax credits mechanically, since grant-funded R&D usually does not qualify for tax credits. At the same time, tax credits can be increasing in grant funding if the grant enables a firm to pursue a new project, which then induces additional R&D expenditures beyond the grant-funded project. This can occur if the firm can hire more R&D labor, for instance. An alternative explanation for a positive relationship is firms strategically relabelling ordinary investment as R&D in order to reap more tax credit benefits, which I address later. I assume that all reported R&D expenditures are actual expenditures in the baseline model.

The effects of ω and $\eta(\omega)$ on the firm's cost of R&D capital can be found by considering a perturbation in the path of a firm's R&D capital stock. The change in after-tax profits resulting from a one unit change in the R&D capital stock for firms behaving optimally is equal to the unit cost of R&D capital, ρ:[6]

$$\rho = (r + \delta)\frac{(1 - \theta\tau - \omega - \eta(\omega))}{1 - \tau}, \tag{2}$$

where δ is the depreciation rate, r is the interest rate, τ is the statutory corporate tax rate applied to firm profits, and θ is the depreciation allowance.[7] This abstracts from adjustment costs, but their inclusion does not affect the theoretical predictions for the main effects of interest.[8]

The marginal effect of grant funding on the cost of R&D is therefore determined not only by its direct effect but also its relationship with tax credits:

[5]Grants can also be a function of tax credits, and all of the results presented here are symmetric, but I include just one dimension of interdependence for expositional purposes.

[6]There are various extensions in the literature. This derivation combines the approach of Bloom et al. (2002) and others for studying R&D tax credits, treating δ as being sensitive to the rate of technical change rather than as an invariant parameter, with the approaches of Ruane (1982) and Criscuolo et al. (2019) for studying direct subsidies.

[7]Depreciation allowances are granted on total R&D investment here, although one can alternatively assume that they are applied to investment net of grants. The cost of R&D capital becomes $\rho = (r + \delta)(1 - \omega - \eta(\omega))$.

[8]Even if the level of grants and tax credits are affected by a firm's marginal adjustment costs somehow—such as by inducing firms to apply for more upfront direct grants in order to overcome start-up costs associated with a new project—this would enhance the magnitude (rather than alter the sign) of the cross price elasticities.

$$\frac{\partial \rho}{\partial \omega} = \frac{-(r+\delta)(1+\frac{\partial \eta}{\partial \omega})}{1-\tau}. \tag{3}$$

Using this expression, the following can be established:[9]

PROPOSITION 1: *The marginal effect of grants on R&D expenditures is unambiguously positive when the two subsidy types are independent* ($\partial\eta/\partial\omega = 0$).

PROOF: When $\partial\eta/\partial\omega = 0$, the effect of grants on the cost of investing in R&D is negative ($\partial\rho/\partial\omega < 0$) by Equation 3, increasing the incentive to invest in R&D.

PROPOSITION 2: *The positive marginal effect of grants on R&D is attenuated when grants and tax credits are substitutes.*

PROOF: When the subsidies are substitutes ($\partial\eta/\partial\omega < 0$), the effect of grants on ρ becomes less negative, reducing the firm's incentive to invest in R&D.

PROPOSITION 3: *The positive marginal effect of grants on R&D is enhanced when grants and tax credits are complements.*

PROOF: When the subsidies are complements ($\partial\eta/\partial\omega > 0$), the effect of grants on ρ becomes more negative, increasing the firm's incentive to invest in R&D.

The empirical tests carried out throughout this paper entail estimating how changes in tax credit rates impact the marginal effect of grants. Importantly, if the two subsidies are *net* substitutes, $\partial\omega/\partial\eta < 0$ by symmetry, and an increase in tax credits attenuates the marginal effect of grants on R&D expenditures by Proposition 2. Likewise if they are net complements, an increase in tax credits enhances the marginal effect of grants on R&D by Proposition 3.

Lastly, when firms receive both subsidies, there may be increasing returns to total subsidies. But this only occurs when the two subsidies are net complements.

PROPOSITION 4: *There are increasing returns to total subsidies if and only if the subsidies are net complements.*

PROOF: The marginal effect of total subsidies on ρ is the sum of their two effects, such that $\frac{\partial\rho}{\partial\omega} + \frac{\partial\rho}{\partial\eta} = \frac{-(r+\delta)(1+\frac{\partial\eta}{\partial\omega})-r}{1-\tau}$. If the subsidies are independent, $\frac{\partial\rho}{\partial\omega} + \frac{\partial\rho}{\partial\eta} = \frac{-(r+\delta)-r}{1-\tau}$. The marginal effect of total subsidies on ρ is negative, and thus the effect on R&D is positive, but it does not change in either subsidy type.

[9] Note that $\partial\eta/\partial\omega$ embodies both an income and substitution effect, and thus we can measure substitutability by holding income constant.

On the other hand, the negative effect of total subsidies on ρ and positive effect on R&D are enhanced if $\partial\eta/\partial\omega > 0$ and they are attenuated if $\partial\eta/\partial\omega < 0$. As such, the marginal effect of total subsidies on R&D only increases when the subsidies are complements and only decreases when they are substitutes. Likewise, when subsidies are complements or substitutes, they necessarily increase or decrease the returns to total subsidies, respectively.

This setup also provides a direct test for the presence of imperfect capital markets. Firms use internal funds to finance R&D that are available at a constant cost of capital until they are exhausted, turning to external resources thereafter. An unconstrained firm can finance all R&D with internal funds and external private finance. Subsidy substitution will occur only when firms are unconstrained, as they are already investing in all profitable opportunities. However, if firms are not already investing in all profitable opportunities, they must be facing financing constraints. Subsidy complementarity thus implies that firms face high costs of external finance due to capital market imperfections.

One alternative explanation for a positive interaction effect is relabelling of ordinary investments as R&D investment. Subsidies reduce the cost of capital, but if firms are unconstrained and already investing in all profitable opportunities, they have an incentive to relabel ordinary investments as R&D to reap greater benefits. As such, whether complementarity achieves additionality in actual R&D—and whether it implies that firms face financing constraints—requires ruling out expenditure relabelling.

Policy implications.—Governments seek to maximize the utility created from subsidizing private R&D, allocating ω and η to firms subject to some budget constraint. If the subsidies are substitutes and firm costs are sub-modular in ω and η, efficient policy requires there to be only one intervention. On the other hand, both funding sources are required for either to increase R&D investment if firm costs are super-modular in ω and η and the two subsidy types are complements.

3 Institutional Setting

3.1 Innovate UK

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.

The main feature of the program that I exploit is a funding rule that determines grant "rates" (i.e., the proportion of the proposed project costs that is funded by the grant). 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. 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.

3.2 R&D Tax Credits

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. Furthermore, loss-making firms also benefit through a payable tax credit.

The enhancement rates are particularly generous for SMEs, and increasingly so over time. Appendix Table C.1 details all of the components that determine a firm's tax credit rate from 2008 forward. For profit-making firms, the percentage of R&D expenditures that the tax credit subsidizes is equal to the product of the enhancement rate and the corporate tax rate.[10] The same formula applies for loss-making firms except that the corporate tax rate is replaced with the payable credit rate.

Between 2008 and 2017, the enhancement rate increased from 0.75 to 1.30. I exploit changes over time when studying small firms. The first major increase happened in 2011, followed by another big increase in 2012 and smaller changes in later years. I split the years into pre- and post-tax credit rate change periods that correspond to 2008 through 2012 and 2013 through 2017.[11] Using the formula to calculate the tax credit benefit (i.e., the percentage of R&D expenditures that is subsidized), Appendix Table C.1 shows that the credit rate increases by 24% for profit-making firms and 53% for loss-making firms between the pre- and post-tax credit rate increase periods, which averages to a 39% increase.

Another key feature of the policy design is that, as of 2008, the firm size that determines SME status under the R&D tax credit scheme is much larger than it is for all other intents and purposes in the UK. For R&D tax credit purposes only, SMEs are defined as those with fewer than 500 employees and either no more than €100m in sales or no more than €86m in total assets. These thresholds are double those typically used for defining SMEs, which are usually 250 employees, €50m in sales, and €43m in total assets.[12]

Appendix Table C.2 provides the enhancement rates for large firms—those that are over the R&D tax credit SME thresholds—which are much lower than those for firms just under the thresholds. The rates for 2008 through 2014 are included, as this is the period I study when examining larger firms. Although firms with fewer than 500 employees are classified as SMEs here, these are large firms by all other definitions. As such, when I discuss larger firms throughout the paper, I am referring to firms that have more than 250 employees.

I use the SME thresholds for identification in the larger firm analysis. On average, the proportion of R&D that is subsidized for firms over the thresholds is 17 percentage points lower than it is for those under them. Dechezleprêtre, Einiö, Martin, Nguyen and Van Reenen (2016) use these thresholds to study the effects of

[10] Firms with less than £300,000 in profit face a different corporate tax rate in the early years, and then they are the same by 2015, as shown in Appendix Table C.1.

[11] I take 2013 as the first post-change year to account for how a policy change in 2012 would affect the incentive to invest in fiscal year 2012-13, and the 2011 and 2012 changes were both large yet followed by only incremental changes.

[12] There were several other changes to the tax credit policy in 2008, but I focus on 2008 forward to be consistent with what can be studied in the small firm analysis.

the tax credit policy on its own, showing that the more generous rates have positive effects on R&D expenditures and patenting. In this paper, I examine how higher tax credit rates at the thresholds impact the marginal effect of grant funding.

4 Empirical Frameworks and Data

In this section, I describe the two research designs I use to test whether direct grants and tax credits are complements or substitutes for small and larger firms, and I discuss the data used for each analysis. Tests of the identification assumptions are reserved for Sections 5.3 and 6.2.

4.1 Small Firms: A Difference-in-Discontinuities Research Design

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 similar to the one developed in Grembi et al. (2016). This entails using two sources of variation in R&D investment costs created by the UK's funding rules and policy changes: 1) the discontinuity in Innovate UK grant funding rates determined by firm size, and 2) before and after variation associated with when the tax credit rate increases. Intuitively, the diff-in-disc approach essentially tests how an increase in the tax credit rate affects the marginal effect of grant funding. Grembi et al. (2016) show how the diff-in-disc estimator identifies the (local) average treatment effect of an *interaction* like this as long as the identification assumptions described in Section 5.3 are satisfied. This approach thus allows me to recover an estimate of the subsidies' interaction effect that can be interpreted as causal.

I estimate a local linear regression of the following form:

$$\begin{aligned} Y_{it} = \delta_0 + \delta_1 A^*_{it} + J_i(\gamma_0 + \gamma_1 A^*_{it}) + T_t[\alpha_0 + \alpha_1 A^*_{it} + J_i(\beta_0 + \beta_1 A^*_{it})] \\ + \mathbf{X}_{it}\phi + \gamma_i + \delta_{ts} + \varepsilon_{it}, \end{aligned} \tag{4}$$

where Y_{it} is the outcome variable for firm i (primarily R&D expenditures), J_{it} is an indicator for grant rate treatment status equal to 1 if firm i's (lagged) employment is less than 50 when receiving a grant and 0 otherwise, T_t is an indicator equal to 1 in the tax credit rate increase post-treatment period (2013-2017) and zero in the pre-treatment period (2008-2012), and ε_i is the random error.[13] The (lagged) employment function, $A^*_i = A_i - A_c$, is normalized at the cutoff point of the running variable, A_c. The slope of the employment function is allowed to differ on each side of the cutoff following the standard approach for regression discontinuity designs

[13] I use lagged employment since grant awards are determined when the project proposal is submitted and reviewed, and competitions typically span two calendar years.

(Imbens and Lemieux 2008). I use employment as the running variable since it is the binding eligibility criteria, however it is not the only determinant of whether firms benefit from a higher grant rate. Firms also must have no more than €10m in turnover or total assets. I account for this by limiting the estimation sample to include only those with lagged turnover or total assets under those thresholds.

I estimate this model around the 50 employee cutoff point using varying sample windows, restricting the data to $A_{it} \in [A_c - h, A_c + h]$, where h represents a distance from the threshold. Throughout the analysis, I include observations for the year in which the firm receives a grant as well as the two years that follow. I consider firms treated for all three years if the firm is eligible for the more generous grant rate when it wins the grant.[14] All running variable components of Equation 4 also use employment from the year prior to receiving a grant, and then current employment is included as an additional control variable.

I include a number of other controls. Firm-level fixed effects, γ_i, account for unobservable differences in R&D investment patterns across firms. Year-by-industry fixed effects, δ_{ts}, control for macroeconomic shocks in year t that can differ by industry s, which is particularly important in this setting because the pre-treatment period includes years just after the great recession. The matrix $\mathbf{X}_{it}$ includes total assets and current liabilities. Standard errors are clustered by industry, defined as the first two digits of the firm's standard industrial classification (SIC) code.

The main coefficient of interest is β_0, the diff-in-disc estimator, identifying the difference between the marginal effects of grant funding in the pre- and post-treatment periods, whereby the marginal effect of grant funding is identified by the discontinuity in funding rates at the employment threshold. The intuition is that the diff-in-disc is positive when increases in tax credit rates enhance the effect of grant funding, indicating that the two subsidy types are complements. Likewise, they are substitutes if the estimate is negative and independent if it is zero.

Although higher-degree polynomials of the running variable are sometimes used in regression discontinuity designs (RDDs), the current best practice is to take a local linear estimation approach (Gelman and Imbens 2017). I use linear polynomials throughout most of the analyses but I show that the results are robust to using higher order polynomials and widening the window around the threshold.

4.1.1 Data for Small Firm Analysis

I use two data sources to study small firms. Innovate UK's Transparency Database provides information on all grants distributed by the program, including details such

[14] As noted, the figures preceding the grant year define treatment status. Since I include two years after firms receive grants, treatment status in those years must align with that which defined the grant rate eligibility status.

as the grant amount award, total proposed project costs, and grant competition year. It also includes company registration numbers (CRNs) so that firms can be uniquely identified and matched to Bureau van Dijk's Financial Analysis Made Easy (FAME) database. This is a commercial database containing detailed administrative data on about 11 million companies and unincorporated businesses in the UK and Ireland. It includes official filings content from Companies House and is enriched with additional efforts to ensure accuracy. In addition to R&D expenditures and the variables required for defining grant rate eligibility, it also provides many other balance sheet details, such as cash flows, liabilities, ordinary investments, and more.

I limit the sample to grants given in 2008 or later. This is for two reasons. There are relatively few grants given through Innovate UK in 2005-2007 relative to later years. Second, doing so avoids selection issues associated with firms that survived the great recession. Including observations from years prior may bias the results if firms that survived differ systematically from those that did not in ways that affect a firm's propensity to invest in R&D.

Of the 10,787 firm-year observations in the final Innovate UK data set, only 353 do not have matches in FAME. This is a 97% match rate and results in 10,434 observations across 6,479 unique firms, with each firm receiving 1.6 grants on average. As detailed in Appendix A, I take a few final steps to prepare the data, such as dropping observations with clear data entry errors. To ensure the results are not driven by outliers, I trim the sample by dropping the top one percent of the R&D investment distribution in the baseline estimation sample. This addresses the concern that innovation investments can be highly volatile (Bronzini and Iachini 2014).

I assume all missing R&D expenditure data represent zero investment beyond the grant-funded project, since firms must report such R&D to receive tax credits. The tax credit has been in place for a long time, so firms are well aware of it, and it is generous and salient.[15] Rational firms apply for it as long as the cost of doing so does not exceed the benefits, which is very unlikely for R&D-intensive firms, especially since it is not a major burden to apply. It simply entails an extra form when filing taxes.

Appendix Table C.3 presents descriptive statistics of the final prepared data, covering firm-year observations 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 data set includes 10,029 grants given to 6,340 firms. For firms with 20 to 80 employees, the baseline sub-sample used throughout the analysis, there are 737 grants given to 544 unique firms. Annual R&D expenditures are about £196,000 on average, which capture expenditures beyond those that are funded by direct grants, since grant-funded R&D does not qualify for tax credits

[15] Conversations with small firms in the UK confirm that this is a sound assumption.

and is thus not reported.

4.2 Larger Firms: A Difference-in-Effects Research Design

To study larger firms, I exploit the 500 employee threshold of the R&D tax credit scheme, whereby firms under the cutoff benefit from higher tax credit rates than those above it from 2008 onward. I use employment as the running variable to be consistent with the small firm analysis.[16] While this threshold could also identify the effect of the tax credit policy alone, I use it to estimate the effect of its interaction with direct subsidies.[17] To do so, I estimate the effect of total direct subsidy funding using ordinary least squares (OLS) separately below and above the threshold, limiting the sample to a narrow window around the threshold, and I calculate the difference in effects at the cutoff to capture the interaction.

The 500 employee cutoff generates a sharp discontinuity in the cost of investing in R&D that does not align with any thresholds associated with other policies affecting firms' investment incentives. Small- and medium-sized enterprises do often benefit more than large firms under other UK policies, but the standard employment, turnover, and total assets thresholds that apply for defining SMEs in all other cases are half the size of those that are set for the tax credit policy. There are no confounding policies and the exclusion restriction is satisfied for estimating a local average treatment effect at the employment cutoff.

Contrary to a typical heterogeneity analysis, calculating the difference in grant effects at the tax credit threshold allows for a causal interpretation of the interaction, even though the direct effects of funding cannot be identified. The difference in the grant effects is driven strictly by the exogenous variation in the tax credit rate. If the effect of grant funding for firms just below the threshold is higher than the effect of grant funding for firms just above it, this means that more generous tax credits enhance the effect of grants and the two subsidy types are complements. If it is lower, they are substitutes, as the more generous tax credits then dampen the marginal effect of grants. This approach provides a test of subsidy complementarity as long as the endogeneity of grant funding does not differ systematically at the tax credit threshold. One of the main identifying assumptions, therefore, is that the endogeneity of grant funding is similar in magnitude and direction on each side of the 500 employee threshold within a narrow window around it. The other identifying assumptions are those that typically apply for a regression discontinuity design. I provide tests in Section 6.2 to confirm that the assumptions hold.

Limiting the sample to include firms only within narrow windows around the

[16] Using just one of the three eligibility criteria as the running variable does not violate any assumptions associated with a regression discontinuity design.

[17] Dechezleprêtre et al. (2016) estimate the effect of the tax credit using a similar strategy but different running variable. They do not estimate the interaction with direct subsidies.

tax credit rate threshold, I estimate the following model separately for firms just below and above it:

$$Y_{it} = \alpha + \beta_1 G_{it} + \mathbf{X}_{it}\phi + \gamma_t + \delta_b + \eta_p + \varepsilon_{it}, \tag{5}$$

where Y_{it}, is R&D expenditures for firm i in year t, G_{it} is firm i's direct subsidy funding received in year t, and γ_t are year fixed effects to control for macroeconomic shocks. The running variable—number of employees for firm i in year t—is allowed to differ on each side of the threshold and is included in matrix $\mathbf{X}_{it}$.[18] The specification also controls for time-invariant mean differences in R&D effort across the types of firms that may pursue different R&D activities with business structure fixed effects (δ_b) and product group fixed effects (η_p). Additional controls are included in $\mathbf{X}_{it}$: firm age, driving distance to the United Kingdom's primary funding agency HQ, and the total value of subsidies allocated to each industry-year. Standard errors are clustered by industry, defined as the first two digits of the firm's SIC.

When calculating the difference in the marginal effects of direct subsidy funding on each side of the threshold, I use a simple Z-score to test whether the difference is statistically significant.

4.2.1 Data for Larger Firm Analysis

Since the Innovate UK grant scheme primarily focuses on small and medium-sized firms, 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.

One might be concerned that using different data to study small and large firms is problematic for comparing results. However, both data sets are built from ad-

[18] The tax credit policy requires the firm to meet the eligibility for two years prior to claiming the tax credit. I use just the current level of employment in the baseline model to maintain a larger sample size, but I show that the results hold when using lagged values of employment in the robustness checks that follow.

ministrative data (i.e., the same reported R&D expenditures), and using both helps ensure the results are not biased in other ways. The BERD data apply a stratified sampling approach that provides far more comprehensive coverage of larger firms relative to small firms. Missing small firm data are interpolated, which is done inconsistently across years and identifying which observations contain real versus interpolated data also is not clear in some years. While this does not pose as much of a problem for studying large firms because of the more comprehensive coverage, it does introduce a bias when comparing small and larger firms since interpolated values appear systematically much more frequently for small firms.

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 C.4 provides summary statistics of the final data used to study larger firms. One observation to highlight is that they make, unsurprisingly, much larger R&D investments than small firms. Firms with 250 to 750 employees spend about £1.4 million on R&D on average. Small firms in the Innovate UK dataset with 20 to 80 employees spend about £196,000 beyond their grant-funded R&D on average, and their Innovate UK grants alone are substantially higher than the additional R&D for which they can claim tax credits.

5 Results for Small Firms

5.1 Main Results

Turning to the results, I begin with the small firm analysis in this section and then provide the findings for larger firms in Section 6. To examine the impact of subsidy interactions for small firms, I estimate the diff-in-disc model of Equation 4, limiting the sample to a narrow window around the grant generosity threshold. I include firms that have 20 to 80 employees in the year before they receive a grant—the year in which treatment status is determined—conditional on having also met either the total assets or turnover criteria. Observations for the grant-funded year and the two years that follow are included.

Table 1 provides the results. The diff-in-disc effects are in the first row, capturing the impact of increasing tax credit rates on the marginal effect of grant funding. In Column 1, only the baseline diff-in-disc covariates are included and then fixed effects and control variables are added when moving from left to right. The effects are positive, large, and statistically significant in all cases, and once firm fixed effects are included, the magnitude of the effect becomes stable. Taking Column 5 with all controls as the baseline specification, the marginal effect of grants increases by £460,000 after the tax credit rate increases, on average. This enhancement of the marginal effect of grants indicates that the subsidy types are complements for small firms.

These effects are large in comparison to the £249,000 mean value of R&D expenditures, however they are not unreasonable when considering the magnitude of the tax credit changes. Appendix Table C.1 provides the history of R&D enhancement rates for profit-making firms, payable credits for loss-making firms, and corporate tax rates, all of which determine the R&D tax credit rates as a percentage of R&D expenditures. The enhancement rate increased from an average of 0.90 in the pre-policy period to an average of 1.28 in the post-policy period, which is a percentage point increase that is 3.8 times the 10 percentage point difference in grant rates at the small firm threshold. Taking the average tax credit rates for the pre-policy and post-policy periods, profit-making firms and loss-making firms experienced 24% and 53% increases, respectively, averaging to an increase of 39%.

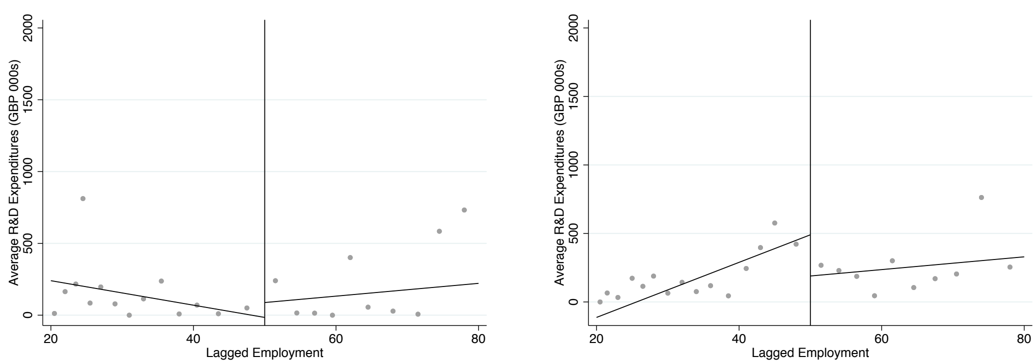
Table 1: Diff-in-Disc Main Results for Small Firms

Outcome Variable:	R&D (1)	R&D (2)	R&D (3)	R&D (4)	R&D (5)
Treated * Post 2012	274.32*	416.20*	421.26**	449.77**	459.85**
	(156.81)	(218.42)	(209.22)	(188.32)	(193.20)
Treated	-12.67	-153.36	-129.48	74.04	45.48
	(126.76)	(345.25)	(343.57)	(341.28)	(350.40)
Post 2012	203.24*	476.19*			
	(104.58)	(241.91)			
Firm FEs		x	x	x	x
Year FEs			x	x	x
Year x Industry FEs				x	x
Controls					x
Observations	1,432	1,299	1,299	1,155	1,147
No. of Firms	561	428	428	389	386
Mean Dep. Var.	213.83	224.77	224.77	249.05	248.90

Notes: Results from estimating Equation 4 for firms that have 20 to 80 employees in the year they win a grant conditional on meeting the total assets or turnover criteria. Observations for the grant year and the two years that follow are included. Treatment and running variables are defined based on employment in the year they win the grant. Dependent variable is total R&D expenditures (£000*s*). Additional controls include (real) total assets and current liabilities. Standard errors are clustered by industry. Asterisks denote $^*p < 0.10$, $^{**}p < 0.05$, $^{***}p < 0.01$.

Figure 1 provides a visual depiction of the difference-in-discontinuity using just the raw data. Each point captures average R&D expenditures for groups of observations around the grant generosity employment threshold for the years before the tax credit rate increases (Panel A) and after (Panel B).[19] There is no clear discontinuity in R&D expenditures at the threshold when tax credits are lower, but R&D expenditures for firms just under the threshold jump substantially once tax credits increase. Intuitively, firms over the small firm threshold also increase R&D effort as tax credits increase, but a clear discontinuity emerges at the threshold relative to the pre-tax credit change period. This jump in the discontinuity illustrates the main findings of Table 1, and the magnitude of the change is similar.

Figure 1: Difference-in-Discontinuity Graphical Results for Small Firms



(a) Pre-Policy Period (2008-2012)

(b) Post-Policy Period (2013-2017)

Note: Average R&D expenditures for groups of firms using the baseline estimating sample. Panel A includes years before tax credits increased and Panel B includes years after.

[19] Bins are created such that they include roughly the same number of observations. The observations included correspond with those in the baseline regressions.

Results from conducting several robustness checks confirm that the estimates in Table 1 are not sensitive to my modelling choices. In Table 2, Column 1 provides the baseline findings for reference and Columns 2-3 provide estimates from when widening the window around the threshold. The magnitudes of the effects decrease as the sub-sample increases, but they are relatively stable in terms of their percentage increases over the sample means. The diff-in-disc effect in the baseline translates into a 185% increase over the sample mean, and those in Columns 2 and 3 reflect 175% and 155% increases over their corresponding sample means. I increase the running variable flexibility to include quadratic and cubic polynomials in Columns 4 and 5 while using the wider window sub-sample. Both the estimates and their statistical significance increase.

Table 2: Wider Windows Around Threshold and Increasingly Flexible Polynomials

Sample:	Baseline	10 to 90 Empl.	<100 Empl.	<100 Empl.	<100 Empl.
Outcome Variable:	R&D	R&D	R&D	R&D	R&D
	(1)	(2)	(3)	(4)	(5)
Treated * Post 2012	459.85**	402.25**	337.52*	418.60**	693.86***
	(193.20)	(183.07)	(189.03)	(189.97)	(220.85)
Treated	45.48	136.35	121.68	160.87	-177.28
	(350.40)	(193.32)	(163.84)	(157.44)	(399.18)
Firm FEs	x	x	x	x	x
Year FEs	x	x	x	x	x
Year x Industry FEs	x	x	x	x	x
Controls	x	x	x	x	x
Linear	x	x	x		
Quadratic				x	
Cubic					x
Observations	1,147	1,759	2,391	2,391	2,391
No. of Firms	386	595	838	383	838
Mean Dep. Var.	248.90	229.69	218.31	218.31	218.31

Notes: Results from estimating Equation 4 and including firms within varying windows around the threshold in the year that they receive grants conditional on meeting the total assets or turnover criteria. Increasingly flexible polynomials of the running variable are included in Columns 4-5. Dependent variable is total R&D expenditures (£000*s*). Additional controls include (real) total assets and current liabilities. Standard errors are clustered by industry. Asterisks denote *p <0.10, **p <0.05, ***p <0.01.

Lastly, in the baseline specifications, I assumed that all missing R&D expenditures data could be interpreted as zeros. Values should indeed appear if firms actually receive tax credits, since expenditures must be reported in order to claim them. To be sure that this assumption doesn't drive the results, though, I also estimate the same specifications of Table 1 but assuming that missing values are zeros only if the firm *never* reports a positive value for R&D expenditures. Appendix Table C.5 provides the results. The magnitudes increase but the percentage changes relative to the sample means are similar to those found when using the original measure of R&D expenditures, ranging from 147% to 170% once including at least firm fixed effects.

5.2 Additionality and Firm Productivity

Firms have an incentive to relabel ordinary investments as R&D when tax credits for R&D increase, particularly when they are unconstrained and are already investing in all profitable opportunities. If they engage in such relabelling, the positive effects that I'm finding may not actually reflect real increases in innovative activity. This is a concern that is often raised in the literature (Hall and Van Reenen 2000).

To ensure that the increases in R&D are real, I estimate the diff-in-disc model with ordinary investments as the dependent variable, as investments should decrease in response to the subsidies if firms are relabelling. Following Zetlin-Jones and Shourideh (2017), I measure investment as the change in tangible assets relative to the preceding year plus depreciation. Column 1 of Table 3 provides the results. There is no offsetting negative effect on investment. Firms also might pass through subsidy or tax credit funding to shareholders when they don't use it for actual R&D (Hall and Lerner 2010), so I also test whether shareholder funds increase. Column 2 of Table 3 shows shareholder funds do not change, providing evidence that such pass-through does not occur.

Finally, I explore whether additional R&D expenditures improve productivity, which achieves two objectives. It further corroborates that firms do not relabel ordinary investments as R&D, as there should be no productivity effects if firms are not actually engaging in more innovative activity, and it provides evidence that the R&D is translating into innovation. The results are presented in Columns 3-6 of Table 3. Both labor and capital productivity—defined as the log of (real) revenue divided by employment and total assets—increase substantially. The subsidy interaction increases labor productivity by 17% and capital productivity by 32%. Column 5 shows that this is not due to a reallocation of inputs, so it must be that enhanced productivity is achieved through innovative activity.

Table 3: Evidence of Additionality and No Expenditure Relabelling

	No Relabelling		Increase in Productivity		
	Investment	Shareholders	Log(Labor Productivity)	Log(Capital Productivity)	Log(K-L Ratio)
	(1)	(2)	(3)	(4)	(5)
Treated * Post 2012	1.05	1.51	0.17*	0.32*	-0.13
	(0.66)	(1.61)	(0.09)	(0.17)	(0.17)
Treated	-1.18	-2.28	-0.10	0.08	-0.23
	(0.75)	(2.91)	(0.20)	(0.29)	(0.15)
Firm FEs	x	x	x	x	x
Year FEs	x	x	x	x	x
Year x Industry FEs	x	x	x	x	x
Controls	x	x	x	x	x
Observations	1,099	1,147	971	971	1,147
No. of Firms	373	386	313	313	386
Mean Dep. Var.	0.32	0.88	4.43	-0.16	4.54

Notes: Results from estimating Equation 4 for firms that have 20 to 80 employees in the year they win a grant conditional on meeting the total assets or turnover criteria. Observations for the grant year and the two years that follow are included. Treatment and running variables are defined based on employment in the year they win the grant. Labor and capital productivity are defined as revenue over employees and (real) total assets, respectively. Findings show that there is no decrease in ordinary investments (Column 1) and firms do not pass through subsidies to shareholders (Column 2). Columns 3-4 show that both labor and capital productivity increase, and this is not explained by a reallocation of inputs (Column 5). Additional controls include (real) total assets and current liabilities. Standard errors are clustered by industry. Asterisks denote *p <0.10, **p <0.05, ***p <0.01.

5.3 Validity of Research Design for Small Firms

The diff-in-disc results provide average treatment effects in the neighborhood of the small firm employment threshold. To interpret these as causal, two identification assumptions must be valid. Potential outcomes must be continuous in employment across the firm size threshold, and there cannot be any confounding policies at the threshold.

To address the first assumption, I conduct a series of tests to ensure that firms do not select into higher grant rates by manipulating the factors that determine eligibility and that firm sorting does not arise when tax credit rates increase. I begin by examining whether there is a *difference* in the firm size density at the 50 employee threshold before and after tax credits increase. If firms manipulate their firm size to select into higher grant rates, we would expect to see "bunching" just below the 50 employee threshold in either period. If they begin manipulating their size in response to the higher tax credit rates, we should see a change in the discontinuity. Appendix Figure B.1 provides scatter plots of firms based on their employment levels with third-order polynomial fits when using the estimation sample and including observations from 2008 through 2012 in Panel A and those from 2013 to 2017 in Panel B. Firms do not appear to manipulate their size in either period and there is no jump in the difference between the two densities. I conduct McCrary density tests for each period and test whether any differences are statistically significant as well. Each discontinuity as well as the difference in discontinuities are statistically zero, indicating that firms do not manipulate firm size in either period nor does sorting arise over time.[20]

Another way in which firms could select into higher grant rates is by manipulating the content of their project proposals. While the difference in grant rates is always 10 percentage points, the proportion of project costs that is subsidized depends on whether the project is for basic, applied, or experimental research. Firms also might propose costs that are higher than those that they will actually incur. There is little room for this to occur given the strong monitoring practices that Innovate UK enforces, but some firms might be particularly savvy. To rule out proposal manipulation, I estimate the diff-in-disc effects when including fixed effects for the project's R&D type category and while controlling for the proposed project cost directly. The results are provided in Columns 1 and 2 of Appendix Table C.6. The results remain almost precisely the same as the baseline estimates and are statistically significant at the 5% level.

I perform additional falsification tests to ensure that the results do not arise

[20]The log difference in the density height is 0.389 with a standard error of 0.347 in the 2008-12 period and it is 0.287 with a standard error of 0.163 in the 2013-17 period. Conducting a t-test for statistical significance of their difference produces a t-statistic of 0.266.

by chance. As a placebo test, I impose pseudo-thresholds and estimate the diff-in-disc model. Expenditures should be smooth across these thresholds, since subsidies do not alter the cost of investing in R&D at these arbitrary cutoffs. Statistically significant discontinuities would suggest that the main results are simply an artifact of the data. Columns 3 and 4 in Appendix Table C.6 provide the findings for when using 30 and 70 employee cutoffs. The effects are small in magnitude relative to the baseline estimates and no where near being statistically significant.

Furthermore, I check whether there are any differences in other covariates at the threshold in the pre-policy period to provide reassurance that the firm size cutoff was not determined based on endogenous firm characteristics. Using the pre-policy data only, I estimate the effects of the discontinuity on total assets, current liabilities, short-run debt, operating profits, available funds (before-tax profits plus depreciation), and the liquidity ratio. The regressions also include the running variable, which differs on each side of the threshold following the usual practice for a regression discontinuity design, as well as year-by-industry fixed effects. Appendix Table C.7 provides the results. There are no statistically significant differences in any of the pre-policy covariates.

Lastly, for the second identification assumption to hold, there must not have been any policies that were introduced or revised in 2012/13 that could have affected firms differentially around the small firm size threshold. The lack of firm size manipulation already suggests that this is true, since any meaningful policy with the same thresholds in place could have induced sorting.[21] However, I also manually reviewed many UK programs and policies to confirm. Details are provided in Appendix Table C.8. Policies providing special benefits to firms of a specific size tend to be for both small- and medium-sized enterprises.[22] For those that are specific to small firms, "small" is defined based on other criteria depending on the specific policy. With no policies having thresholds that align, no changes in policies could have differentially affected firms around the grant rate threshold.

6 Results for Large Firms

6.1 Main Results

Turning to the findings for larger firms, Table 4 provides the main results from estimating the effect of direct subsidies on R&D expenditures by Equation 5 separately on each side of the tax credit generosity threshold. The effects for firms benefiting from the higher tax credits are presented in odd-numbered columns and those that

[21] For instance, many labor laws start to bind for firms with more than 50 employees in France, and this results in bunching just below the 50 employee threshold (Garicano, Lelarge and Van Reenen 2016).

[22] SMEs are generally defined as those with fewer than 250 employees.

are only eligible for the lower rate are in even-numbered columns for various subsets of data around the threshold. The main estimates of interest are those in the bottom row, which capture the difference in the effect of direct subsidies for those receiving more or less generous tax credits.

The differences in effects are negative and large in magnitude. The 17 percentage point higher tax credit rate cuts the effect of grants in half in the most conservative case (Columns 3 and 4), and the differences are statistically significant at the 1% or 5% level in all cases. While the marginal effects of grants on their own should not be interpreted as causal, the difference at the threshold is driven strictly by the tax credit generosity threshold, providing an estimate of the causal interaction effect as long as the endogeneity of grant funding moves in the same direction and with a similar magnitude on each side of the threshold.[23] The key takeaway is that higher tax credit rates substantially dampen the marginal effect of grants, and thus the two mechanisms are substitutes for larger firms.

[23] I discuss this further in Section 6.2

Table 4: Main Results for Larger Firms

Sample:	150 to 850 empl.		250 to 750 empl.		350 to 650 empl.	
	<500	$\geq$ 500	<500	$\geq$ 500	<500	$\geq$ 500
Outcome Variable:	R&D	R&D	R&D	R&D	R&D	R&D
	(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 (odd-numbered columns) and above (even-numbered columns) the tax credit generosity threshold for varying sub-samples of data. In Columns 1 and 2, firms with 150 to 850 employees are included. Firms with 250 to 750 employees are included in Columns 3 and 4, and firms with 350 to 650 employees are included in Columns 5 and 6. 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.

To provide further confidence that the differences in grant effects are indeed driven by the difference in tax credit generosity, I conduct the same analysis for capital and non-capital R&D expenditures separately. Most R&D capital expenditures do not qualify for tax credits in the UK. Rather, the majority of eligible expenditures are non-capital expenditures, like those for R&D labor. As such, the substitution effect should primarily occur for non-capital expenditures. This is exactly the case. Table 5 shows that the marginal effect of grants is cut in half for non-capital expenditures but there is no interaction effect at all for capital expenditures. These findings for non-capital expenditures fully explain the main result. Firms with 250 to 750 employees are included in these regressions, and the magnitude of the substitution effect aligns almost precisely with the estimates in Columns 3 and 4 of Table 4.

Table 5: Effects on Capital vs. Non-Capital R&D Expenditures for Larger Firms

Outcome Variable:	Capital R&D Expenditures		Non-Capital R&D Expenditures	
	<500 Empl.	≥500 Empl.	<500 Empl.	≥500 Empl.
	(1)	(2)	(3)	(4)
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) R&D expenditures. Capital expenditures include those on land, buildings, equipment, and machinery. Non-capital expenditures mostly include 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. The final row shows how the difference in effects at the threshold are driven entirely by a reduction in non-capital R&D expenditures, as expected since the tax credits do not apply to capital R&D investments. 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.

6.2 Validity of Research Design for Large Firms

Validity of the research design for large firms rests on three identification assumptions. First, there must not be any other policies that generate different incentives for firms at the thresholds determining tax credit generosity. In Section 4.2, I described how this is the case, as the firm size thresholds under the R&D tax credit scheme are double those that determine SME status in all other circumstances.

Second, firms must not be selecting into the higher tax credit rates. To ensure that selection bias is not a concern, I start by checking whether firms appear to manipulate their size so that they fall below the 500 employee threshold. Savvy firms exhibiting this behavior may differ systematically from those that do not manipulate their size, making firms just above the threshold a poor control group. Figure B.2 plots the firm size distribution density for firms with 250 to 750 employees. There is no discontinuity at the 500 employee threshold and a McCrary test confirms that there is no statistically significant discontinuity.[24]

I also test for continuity in observable covariates around the threshold in pre-policy years, which provides confidence that the cutoff was randomly selected and that firms around the cutoff are not systematically different. Table C.9 presents mean values for several variables in years prior to 2008. I test for statistically significant differences using t-tests in covariate means. There are no statistically significant differences across the various measures shown. Expenditures on R&D in the pre-policy period did not differ, as expected, since the threshold did not yet exist. There are also no statistically significant differences in the proportion of R&D that is funded by direct subsidies, turnover per employee, or expenditures specifically on basic and applied research, indicating the firms did not differ systematically before the tax credit threshold was implemented.

The final identification assumption is that the endogeneity of grant funding is of a similar magnitude and moves in the same direction for firms just below and above the tax credit threshold. The preceding tests confirming that the threshold was selected at random and that firms do not select into higher rates also confirm that this assumption holds. One of the primary concerns with grant funding being endogenous is that more innovative firms—those investing more in R&D—are those that are also more likely to win grant competitions. When calculating the difference in grant effects at the threshold, this is only an issue if firms are systematically more or less innovative on one side of the threshold. The covariate balance tests in Appendix Table C.9 show that the proportion of R&D expenditures that is funded by direct grants is exactly the same for firms under and over the threshold (4%), and there are no statistically significant differences in other covariates. This suggests that endogeneity in grant funding is likely similar for firms just below and above

[24]The log difference in density height is -0.108 with a standard error of 0.323.

the threshold.

I conduct a few final robustness checks. First, I test whether the effect of grants is continuous across arbitrary pseudo-thresholds where there is no difference in the tax credit rates to ensure that the difference in grant effects does not just occur randomly by chance. These results are presented in Table C.10 when imposing cutoffs at 200, 250, 750, and 800 employees. There are no interaction effects detected. The differences in grant effects are extremely small in magnitude relative to the baseline results, and they are no where near being statistically significant.

Furthermore, although I only use the current year's employment to define tax credit generosity treatment in the baseline estimation to preserve sample size, eligibility formally requires firms to fall under the thresholds for two consecutive years.[25] Appendix Table C.11 presents results when defining tax credit generosity status according to the preceding years' employment as well. Columns 1 and 2 use just the previous year's employment, Columns 3 and 4 use both the current year and the previous year, and Columns 5 and 6 use the current year and the two previous years. The negative interaction effects become even larger, and thus the magnitude of the main results is conservative, if anything.

Lastly, I use increasingly flexible running variables and provide the results in Appendix Table C.12. The baseline results are provided in Columns 1 and 2 for reference, quadratic polynomials are used in Columns 3 and 4, and cubic polynomials are included in Columns 5 and 6. The results barely change. The grant effect is still cut almost precisely in half, indicating that the results are not driven by the polynomial flexibility modelling choice.

7 Mechanism and Implications

The main result of this paper—that direct grants and tax credits for R&D are complements for small firms and substitutes for large firms—has important policy implications regardless of the channel through this occurs. Nonetheless, confirming the underlying mechanisms can yield additional insight on how policy can address inefficiencies. The theory developed in Section 2 demonstrates how direct subsidies and tax credits can only be complements if firms face financing constraints, absent relabelling of ordinary investments as R&D expenditures. The evidence provided in Table 3 rules out such relabelling. In this section, I provide further evidence of there being imperfect capital markets and discuss the implications.

[25] The panel is unbalanced, so relying on too many years of lagged values reduces the sample size.

7.1 Evidence of Imperfect Capital Markets

Small firms may face financing constraints for a variety of reasons. For instance, there may be information asymmetries, whereby external investors have insufficient knowledge about a firm's ability to develop a new technology. This could occur if the firm hasn't yet invested in the particular space that it's pursuing, and thus investors may perceive the project or firm as a risky investment. Firms will then face a high cost of capital or not secure external finance at all.

I provide three sets of results that are consistent with financing constraints being the driver of subsidy complementarity. Since the effects should be larger for constrained firms, as they are more sensitive to cash flow shocks, I estimate the baseline diff-in-disc model of Equation 4 separately for firms that appear to be more or less constrained according to three balance sheet items: short-term loans and overdrafts, before-tax profits, and "available funds".

Firms with financing constraints are more likely to have short-term debt, as these types of loans are typically sought when firms do not have internal funds to cover unexpected costs. Columns 1 and 2 in Table 6 provide the results from estimating the effects for firms under and over the median value in the baseline estimating sample.[26] The effect is positive and statistically significant only for those that are more constrained. Second, firms with lower profits have fewer resources for financing innovation internally. I estimate the effects for firms with before-tax profits below and above the median value in the baseline sample (Columns 3 and 4), and the findings show that the effect is large and positive only for those that are more constrained. Third, I follow the approach of Zetlin-Jones and Shourideh (2017) for measuring available funds as the sum of profits and depreciation, which capture internal resources available for investment. Once again, the effects are driven entirely by firms that are more constrained (Columns 5 and 6).

[26]Note that these are recorded as liabilities on firm balance sheets, so a lower mean value in the sample is associated with being more constrained.

Table 6: Evidence that Small Firms Face Financing Constraints

Outcome Variable:	Short Term Debt		Before-Tax Profit		Available Funds	
	Constrained	Unconstr.	Constrained	Unconstr.	Constrained	Unconstr.
	(1)	(2)	(3)	(4)	(5)	(6)
Treated * Post 2012	853.78*	-260.14	1869.41**	106.02	1635.36**	572.94
	(452.75)	(647.29)	(758.69)	(441.06)	(717.88)	(448.76)
Treated	468.00	455.18	-1095.00	163.89	-875.50	-597.21
	(423.22)	(664.54)	(884.51)	(515.47)	(777.36)	(485.56)
Firm FEs	x	x	x	x	x	x
Year FEs	x	x	x	x	x	x
Year x Industry FEs	x	x	x	x	x	x
Controls	x	x	x	x	x	x
Observations	343	597	287	610	350	549
No. of Firms	122	214	98	235	123	218
Mean Dep. Var.	250.27	278.84	582.73	119.99	543.12	106.24

Notes: Results from estimating Equation 4 with dependent variables that proxy for financing constraints: short-term debt, before-tax profits, and available funds as measured by the sum of before-tax profits and depreciation. Constrained firms are those that have more debt, less profit, and fewer available funds than the baseline sample's median values. Constrained firms are included in the odd-numbered columns and less constrained firms are in even-numbered columns. Additional controls include (real) total assets and current liabilities. Financial variables are in real terms (*£000s*). Standard errors are clustered by industry. Asterisks denote *p <0.10, **p <0.05, ***p <0.01.

7.2 Policy Implications

Taken together, my findings suggest that both grants and tax credits should be available for small firms only, as they are complements for small firms but substitutes for large firms. When subsidies are complements, both are required for either to be effective. On the other hand, providing both to large firms will result in the subsidization of infra-marginal expenditures, since these firms are unconstrained and already investing in all profitable opportunities.

My research designs and data allowed me to study the effects of additional grant funding on firms that receive grants, and understanding the effects of receiving a grant in the first place is also important for policy. It's worth highlighting that my subsidy interaction estimates can be interpreted as lower bounds in the small firm analysis, though, since winning a grant in the first place entails receiving more total funding than the 10 percentage point difference. The effects of receiving a grant should thus be even larger, and especially if they induce firm entry, as direct grants tend to be most useful for small firms facing financing constraints and first time recipients (Howell 2017; Howell, Rathje, Van Reenen and Wong 2020). It's possible that the negative interaction effects for larger firms would be attenuated when considering the receipt of a grant rather than funding levels, but only if large firms are constrained. This is not very likely considering how larger firms are more likely to have more internal resources as well as a longer history of success to help secure external private investment.

8 Conclusion

The primary novel insight of this paper is that R&D grants and tax credits interact in their effects on firm behavior. While there is a growing literature demonstrating how each support mechanism has positive effects on innovation when studied on their own, fully evaluating their effects requires accounting for their interdependence. I develop a framework for studying this phenomenon, which also provides a direct test for detecting capital market imperfections. I implement two quasi-experimental research designs to study UK firms and show that direct grants and tax credits for R&D are complements for small firms but substitutes for larger firms.

The findings 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 when their effects are not independent, accounting for subsidy interactions in optimal R&D policy design could substantially enhance the efficiency of public spending. The key takeaway is that, in my setting, both support mechanisms must be provided to small firms for either to be effective. Only one should be provided to large firms, or else public funding subsidizes infra-marginal expenditures.

The estimates are local in nature, as is always the case for the type of research designs implemented in this paper. I overcome this partially by studying both small and large firms, but each analysis is limited to narrower ranges of firm sizes. That said, policymakers often distinguish between small, medium, and large firms when defining tax rates and designing subsidy schemes. My findings therefore may be of interest when policymakers use multiple support mechanisms to support R&D in many contexts. In fact, policy interdependence is common in many other economic settings as well. This paper highlights the importance of developing a better understanding of how such policies interact.

References

Aghion, P. and P. Howitt, "A Model of Growth Through Creative Destruction," *Econometrica*, 1992, *60* (2), 323–351.

_ and _ , *Endogenous Growth Theory*, Cambridge, MA: MIT Press, 1998.

Agrawal, A., C. Rosell, and T. Simcoe, "Tax Credits and Small Firm R&D Spending," *American Economic Journal: Economic Policy*, 2020, *12* (2), 1–21.

Akcigit, U. and W.R. Kerr, "Growth through Heterogeneous Innovations," *Journal of Political Economy*, 2018, *126* (4), 1374–1443.

Arrow, K.J., "The Economic Implications of Learning by Doing," *Review of Economic Studies*, 1962, *29*, 155–173.

Ashraf, N., B.K. Jack, and E. Kamenica, "Information and subsidies: Complements or substitutes?," *Journal of Economic Behavior and Organization*, 2013, *88*, 133–139.

Atkeson, A. and A. Burstein, "Aggregate Implications of Innovation Policy," *Journal of Political Economy*, 2019, *127* (6), 2625–2683.

Autor, D.H. and M.G. Duggan, "The Rise in the Disability Rolls and the Decline in Unemployment," *Quarterly Journal of Economics*, 2003, *118* (1), 157–205.

Azoulay, P., J.S. Graff Zivin, D. Li, and 2018 Sampat B.N., "Public R&D Investments and Private-sector Patenting: Evidence from NIH Funding Rules," *Review of Economic Studies*, 2018.

Bloom, N. and J. van Reenen, "Measuring and Explaining Management Practices Across Firms and Countries," *Quarterly Journal of Economics*, 2007.

_ , E.A. Mahajan, D. McKenzie, and J. Roberts, "Does Management Matter? Evidence from India," *Quarterly Journal of Economics*, 2013, *128* (1), 1–51.

_ , R. Griffith, and J. van Reenen, "Do R&D Tax Credits Work? Evidence from a Panel of Countries 1979-1997," *Journal of Public Economics*, 2002, *85* (1), 1–31.

Bøler, E.A., A. Moxnes, and K.H. Ulltveit-Moe, "R&D, International Sourcing, and the Joint Impact on Firm Performance," *American Economic Review*, 2015, *105* (12), 3704–3739.

Bronzini, R. and E. Iachini, "Are Incentives for R&D Effective? Evidence from a Regression Discontinuity Approach," *American Economic Journal: Economic Policy*, 2014, *6* (4), 100–134.

Criscuolo, C., R. Martin, H. Overman, and J. Van Reenen, "Some Causal Effects of an Industrial Policy," *American Economic Review*, 2019, *109* (1), 48–95.

Dechezleprêtre, A., E. Einiö, R. Martin, K-T. Nguyen, and J. Van Reenen, "Do Tax Incentives for Research Increase Firm Innovation? An RD Design for R&D," *CEP Discussion Paper No. 1413*, 2016.

Duflo, E., P. Dupas, and M. Kremer, "Education, HIV and early fertility: experimental evidence from Kenya," *Mimeo*, 2012.

Dupas, P., "What matters (and what does not) in households' decisions to invest in malaria prevention?," *American Economic Review: Papers and Proceedings*, 2009, *99* (2), 224–230.

Garicano, L., C. Lelarge, and J. Van Reenen, "Firm Size Distortions and the Productivity Distribution: Evidence from France," *American Economic Review*, 2016, *106* (11), 3439–79.

Gelman, A. and G. Imbens, "Why high-order polynomials should not be used in regression discontinuity designs," *Journal of Business & Economic Statistic*, 2017.

Grembi, V., T. Nannicini, and U. Troiano, "Do Fiscal Rules Matter?," *American Economic Journal: Applied Economics*, 2016, *8* (3), 1–30.

Guceri, I. and L. Liu, "Effectiveness of Fiscal Incentives for R&D: Quasi-experimental Evidence," *American Economic Journal: Economic Policy*, 2019, *11* (1), 266–91.

Hall, B.G. and D.W. Jorgenson, "Tax Policy and Investment Behavior," *American Economic Review*, 1967, *57* (3), 391–414.

_ **and J. Lerner**, "The Financing of R&D and Innovation," *Handbook of the Economics of Innovation*, 2010.

Hall, B.H. and J. Van Reenen, "How Effective are Fiscal Incentives for R&D? A Review of the Evidence," *Research Policy*, 2000, *29*, 449–69.

HMRC, "Research and Development Tax Credits Statistics," 2017.

Howell, S., "Financing Innovation: Evidence from R&D Grants," *American Economic Review*, 2017, *107* (4), 1136–1164.

_ **, J. Rathje, J. Van Reenen, and J. Wong**, "Opening up Military Innovation: An Evaluation of Reforms to the U.S. Air Force SBIR Program," *Working Paper*, 2020.

Imbens, G. and T. Lemieux, "Regression Discontinuity Designs: A Guide to Practice," *Journal of Econometrics*, 2008, *142* (2), 615–35.

Inderbitzin, L., S. Staubli, and J. Zweimuller, "Extended Unemployment Benefits and Early Retirement: Program Complementarity and Program Substitution," *American Economic Journal: Economic Policy*, 2016, *8* (1), 253–288.

InnovateUK, "About Us," n.d.

Jones, C., "R&D-Based Models of Economic Growth," *Journal of Political Economy*, 1995, *103* (4), 759–784.

King, M., "Taxation and the Cost of Capital," *Review of Economic Studies*, 1974, *41* (1), 21–35.

Klette, T.J. and S. Kortum, "Innovating Firms and Aggregate Innovation," 2004, *112* (5), 986–1018.

Nelson, R.R., "The Simple Economics of Basic Scientific Research," *Journal of Political Economy*, 1959, pp. 297–306.

Romer, P., "Endogenous Technological Change," *Journal of Political Economy*, 1990, *98.*

Ruane, F., "Corporate Income Tax, Investment Grants, and the Cost of Capital," *Journal of Public Economics*, 1982, *17*, 103–109.

S., Sorenson B.-Villegas-Sanchez C.-Volosovych V. Kalemli-Ozcan and S. Yesiltas, "How to Construct National Representative Firm Level Data from the ORBIS Global Dataset," *Working paper*, 2015.

Segerstrom, P.S., "The Long-Run Growth Effects of R&D Subsidies," *Journal of Economic Growth*, 2000, *5* (3), 277–305.

Syverson, C., "What Determines Productivity?," *Journal of Economic Literature*, 2011, *49* (2), 326–365.

_ , "Challenges to Mismeasurement Explanations for the U.S. Productivity Slowdown," *NBER Working Paper 21974*, 2016.

U., Hanley D. Akcigit and N. Serrano-Velarde, "Back to Basics: Basic Research Spillovers, Innovation Policy and Growth," *Review of Economic Studies*, 2020.

Zetlin-Jones, A. and A. Shourideh, "External financing and the role of financial frictions over the business cycle: Measurement and theory," *Journal of Monetary Economics*, 2017, *92*, 1–15.

Data References

Financial Analysis Made Easy (FAME), Bureau van Dijk. Available at: https://www.bvdinfo.com/en-gb/our-products/data/national/fame

Department for Business, Energy & Industrial Strategy, Innovate UK, UK Research and Innovation. (2017). Transparency Data: Innovate UK funded projects since 2004. Available at: https://www.gov.uk/government/publications/innovate-uk-funded-projects

Office for National Statistics. (2017). Business Expenditure on Research and Development, 1994-2015: Secure Access. [data collection]. 6th Edition. UK Data Service. SN: 6690,
http://doi.org/10.5255/UKDA-SN-6690-6

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

A Appendix: Data Preparation—For Online Publication

This appendix details the process I followed for preparing the data sets and the notable results associated with the matching.

A.1 Data Preparation for Small Firm Analysis

Direct Grants for R&D.—To study small firms, I examine those that receive grants from Innovate UK, the largest public funding body for private sector innovation in the UK. I start by gathering the public database of all grants provided by the program from 2005 to 2017 from Innovate UK's Transparency Database This contains grant information since the program's inception, providing details on the grant amount award, total proposed project costs, and grant year. Most importantly, it includes unique company registration numbers (CRNs) so that firms can be uniquely identified and matched to other data sets that also provide CRNs.

Each observation in the starting data set coincides with a grant, and firms can receive multiple grants, both within a year if they apply to different competitions and over time. I drop observations that are indicated as having been withdrawn, and any case for which the enterprise type is labeled as academic, non-UK, or sole trader, as they would not be eligible for claiming an R&D tax credit. I assume any case in which the grant amount offer or total proposed cost is zero to be missing data, as they cannot be zero in practice and this can be just treated as data that is not entered. I drop cases in which the CRN is missing. I also manually examine the data to drop observations for which the CRN is in a format that does not follow the standard format and consider these to be data entry errors, which is only about 30 observations. I omit grants that are provided as "vouchers", as these are given through a process that does not align with the features that are important for identification in my research design (i.e., all vouchers have the same value). The final step is dropping just a few observations that clearly contain data entry errors, such as those when the listed grant funding amount exceeds total project costs as well as any duplicate observations.

The resulting grant-level data set contains 14,497 grants allocated to 6,737 unique firms from 2005 through 2017—firms thus receive about 2.15 grants on average. Once collapsing to create a firm-year panel data set that can be matched to balance sheet data, there are 10,787 firm-year observations.

Firm R&D Expenditures and Other Balance Sheet Information.—Firm-level R&D expenditures data are obtained from Burean van Dijk's Financial Analysis Made Easy (FAME) Database, which is a commercial data set containing detailed administrative data on companies and unincorporated businesses in the UK and Ireland. It includes official filings content from the UK's Companies House and is enriched with additional efforts to ensure accuracy and providing some additional information. It covers over 11 million companies, including 2 million that are in a detailed format, 1.3 million companies that are active but have not yet filed accounts or are not required to file, and 6 million companies that are no longer active. In addition to including R&D expenditures and the variables required for defining grant rate eligibility (employees, total assets, and turnover), it includes other balance sheet details such as liabilities, cash flows, profits and losses, debt, industrial classification codes, and more.

In the UK, all limited, PLC, LLP and LP companies are required to file accounts, which represent about 1 million companies as of 2015 in FAME (Kalemli-Ozcan and Yesiltas 2015). All companies in the UK must keep accounting records of all money received and expended, assets, and liabilities and file their accounts at Companies House. Small firms can prepare less detailed accounts, however they must still report a profit and loss account and a balance sheet. Although small firms are not required to report R&D expenditures, they must report expenditures beyond their grant-funded R&D in order to claim tax credits. The form is a simple addition to their standard required filings, and thus I assume that firms investing in R&D that is eligible for tax credits report their R&D.

The FAME data provides the latest account date, but some firms report quarterly whereas others report annually. I follow Kalemli-Ozcan and Yesiltas (2015) and define the filing year based on the year of the latest filing date if the date is June 1 or later of that year and otherwise I use the prior year.

Matching Innovate UK Data to FAME.—Of the 10,787 firm-year observations in the final Innovate UK data set, only 353 do not match. This is a 97% match rate and results in 10,434 observations across 6,479 firms. Each firm receives 1.60 grants on average.

Final variable construction.—I take a few final steps to prepare the data set. I omit observations for which the founding year is lower than the current year as well as cases for which R&D, total assets, turnover, employees, the amount of grant offered, the proposed project costs, and actual spending are negative, as these cases reflect data entry error. This results in only 20 observations being dropped. All monetary variables are converted into real 2010 terms using the World Bank's CPI for GBP, and I convert total assets and turnover into euros using each year's average exchange rate, as the Innovate UK generosity thresholds are defined by euros.

I use two alternative measures of R&D expenditures throughout the analysis. In the baseline estimations, I consider all missing R&D data to be zeros since firms must report R&D in order to receive tax credits. I also construct a second measure that considers expenditures missing if the firm *never* reports R&D at all. Although it is highly unlikely that firms would not report R&D if they are eligible, this alternative measure accounts for any cases in which the marginal benefit of reporting does not exceed the marginal cost.

Throughout the analysis, I include observations in the year that the firm receives a grant and two years afterwards to capture longer-lasting effects on the firm's R&D activity. Eligibility for higher grant award rates depends on the employment, total assets, and turnover in the year the firm's proposal is evaluated, though. To define whether the firm is treated by the higher grant rate, I use the values of the year prior to receiving a grant. Innovate UK competitions carry through over two calendar years, and thus I take the first year of the competition year to assess eligibility, assuming that the grant is dispersed during the ending year of the competition. I then assign these lagged values to each year that I include for the firm. That is, if a firm receives a grant in 2015, I use the 2014 values to define treatment and consider the firm treated in 2015, 2016, and 2017. If the firm receives another grant during those years, I then apply the same procedure, and the new values displace the previous ones. These rules then carry through when defining the running variables as well.

To be eligible for the higher grant award rates, they must have fewer than 50 employees and either their total assets or turnover must be lower than 10m euros. I thus include only firms that meet the latter criteria throughout the analysis, and then define a treated firm as those that have fewer than 50 employees. This allows me to take all three eligibility criteria into account, using employment as the running variable since it is the binding criteria. If both turnover and total assets data are missing in the preceding year, I assume that the firm meets the criteria. Conditional on meeting the turnover and assets criteria following this procedure, the panel contains 7,455 observations across 4,849 firms. Firms thus receive 1.54 grants on average, which is just slightly lower than the overall average of 1.60.

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 error. Omitting observations with imputed responses for the key outcome variable of interest (R&D expenditures) reduces the sample size to about 2,500 observations per year. Next, I omit observations where the Inter-Departmental Business Registrar (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 process results in dropping <0.01 percent of the observations.

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, the sample goes from 2,544 observations to 2,497. 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 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 data sets held by the ONS.

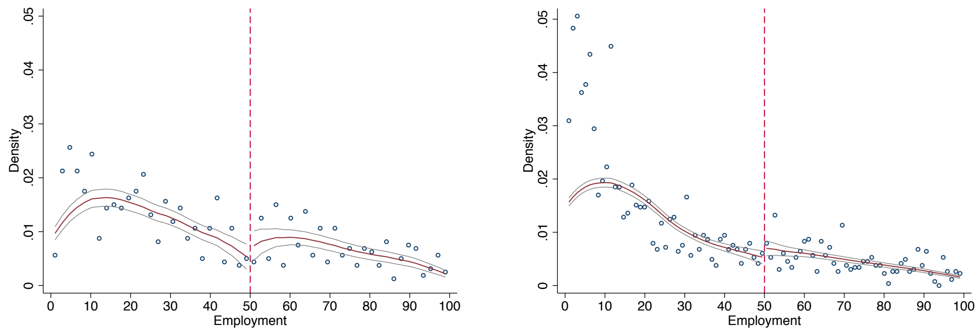
Final Data Sample Preparation.—An additional control variable that I construct is the firm's distance from the UK's primary funding agency's headquarters in London. This helps control for knowledge spillovers, since the vast majority of R&D in the

UK happens in or near London. 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 neighborhood of the postcode (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. Applying this procedure using post codes from BERD and BSD provide distance measures for all but 0.1 percent of the BERD data. 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).

A few final steps are taken to prepare the data. 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 sub-sample of the data used includes about 2,000 to 2,500 firms per year from 2000 through 2014.

B Appendix: Additional Figures—For Online Publication

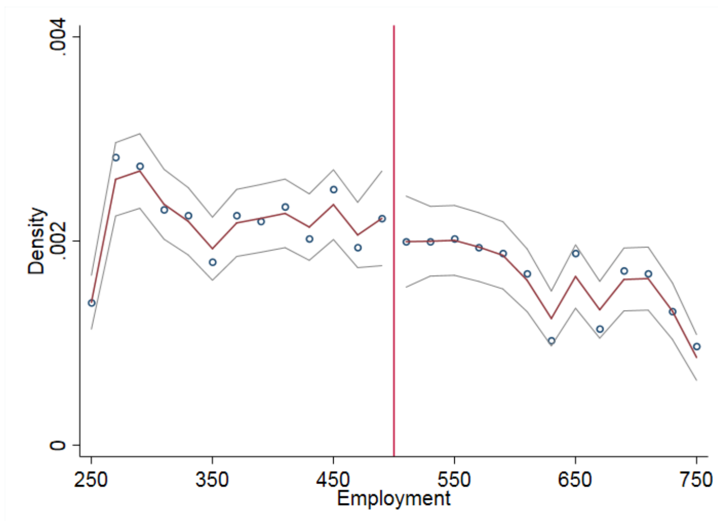
Figure B.1: No Firm Size Manipulation Before or After Tax Credit Change



(a) McCrary Density Test (2008-2012) (b) McCrary Density Test (2013-2017)

Note: McCrary tests for a discontinuity in the distribution density of employment at the small firm employment threshold before the tax credit increased (Panel A) and after (Panel B). Samples include firms with fewer than 100 employees. In Panel A, the log difference in the density height is 0.389 with a standard error of 0.347. In Panel B, the log difference is 0.287 with a standard error of 0.163. Neither difference is statistically significant, and they are not statistically from each other (t-statistic for the difference is 0.266).

Figure B.2: No Firm Size Manipulation at the Tax Credit Generosity Threshold



Note: McCrary test for a discontinuity in the distribution density of total employment at the threshold for firms to receive a more generous tax credit. Sample includes firms with 250 to 750 employees. Log difference in density height of -0.1082 with a standard error of 0.3226.

C Appendix: Additional Tables—For Online Publication

Table C.1: R&D Tax Credit Rates for Small and Medium-Sized Firms

	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Panel A: Enhancement Rates and Corporate Taxes							
Year	Enhancement Rate	Payable Credit	Low Corp. Tax	Main Corp. Tax	Profit-Making % Benefit		Loss-Making % Benefit
					Low Tax	Main Tax	No Tax
2008	0.75	0.14	0.21	0.28	0.16	0.21	0.105
2009	0.75	0.14	0.21	0.28	0.16	0.21	0.105
2010	0.75	0.14	0.21	0.28	0.16	0.21	0.105
2011	1.00	0.125	0.20	0.26	0.20	0.26	0.125
2012	1.25	0.11	0.20	0.24	0.25	0.30	0.138
2013	1.25	0.11	0.20	0.23	0.25	0.29	0.138
2014	1.25	0.145	0.20	0.21	0.25	0.26	0.181
2015	1.30	0.145	0.20	0.20	0.26	0.26	0.189
2016	1.30	0.145	0.20	0.20	0.26	0.26	0.189
2017	1.30	0.145	0.19	0.19	0.25	0.25	0.189

Panel B: Average Tax Credit Benefits and Changes

	2008-2012	2013-2017	% Change
Profit-making	0.21	0.26	24%
Loss-making	0.12	0.18	53%
Average	**0.165**	**0.22**	**39%**

Notes: Table provides R&D enhancement rates and corporate tax rates (Columns 1-4 in Panel A), which determine the R&D benefits (Columns 5-7 in Panel A). The R&D benefit is determined by whether the firm is loss-making and thus qualifies for the payable credit or profit-making and thus qualifies for the tax credit. For profit-making firms, the benefit depends on whether they make less than 300k in profits or more than 300k in profits, whereby they face the low corporate tax rate in the former case and the main tax rate in the latter case. The percent benefits of the tax credits is calculated as the product of the enhancement rate and corporate tax rate for profit-making firms and the enhancement rate times the payable credit for loss-making firms. Panel B provides the average rates for profit-making and loss-making benefits during the pre- and post-policy change years, the percentage changes, and the average percentage change.

Table C.2: R&D Tax Credit Rates for Large Firms

	(1)	(2)	(3)	(4)
Year	**Enhancement Rate**	**Corp. Tax**	**% Benefit**	**Percentage Point Difference from SMEs**
2008	0.3	0.28	0.084	-0.13
2009	0.3	0.28	0.084	-0.13
2010	0.3	0.28	0.084	-0.13
2011	0.3	0.26	0.078	-0.18
2012	0.3	0.24	0.072	-0.23
2013	0.3	0.23	0.069	-0.22
2014	0.3	0.21	0.063	-0.20

Notes: Table provides R&D enhancement rates for firms over 500 employees, the main corporate tax rate, the percent R&D tax credit benefit that this translates into, and the percentage point difference in benefits relative to SMEs paying the main corporate tax rate. The tax credit rate is the product of the enhancement and corporate tax rates. On average through this period, firms qualifying as SMEs benefited from tax credit rates that were 17 percentage points higher.

Table C.3: Innovate UK Grant Awards and Small Firms' R&D

	Full Sample	<100 Empl.	20 to 80 Empl.
	(1)	(2)	(3)
Panel A: Grant Awards			
No. of Unique Grants	10,029	1,818	737
No. of Unique Firms	6,340	1,392	544
Panel B: Funding Levels			
Grant Amount (£000s)	£227.49	£209.46	£238.63
	(£1,363)	(£380.42)	(£438.42)
Total Project Cost Funded (%)	57.8%	60.2%	55.9%
	(17.9%)	(17.2%)	(17.7%)
No. of Observations	9,913	1,806	731
Panel C: Outcome Variable			
R&D Expenditures (£000s)	£166.33	£133.76	£195.97
	(£938.82)	(£708.28)	(£848.29)
No. of Observations	22,071	3,378	1,563

Notes: Table provides descriptive statistics for firms receiving Innovate UK grants between 2008 and 2017. 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. Only firm-year observations when grants are received from 2008 to 2017 are included in Panels A and B. In Panel C, observations for the two years following a grant are also included, consistent with the baseline estimation sample.

Table C.4: Direct Subsidy and Outcome Descriptive Statistics, Larger Firms

	Wide Window (150 to 850) (1)	Midrange Window (250 to 750) (2)	Narrow Window (350 to 650) (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)
Prop. of R&D 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 2009 through 2014 for firms receiving direct subsidies.

Table C.5: Small Firm Diff-in-Disc Results for Alternative Measure of R&D

Outcome Variable:	R&D (1)	R&D (2)	R&D (3)	R&D (4)	R&D (5)
Treated * Post 2012	571.73*	814.99*	857.72**	846.90**	813.92**
	(293.30)	(401.16)	(386.54)	(293.48)	(313.67)
Treated	-64.21	-243.18	-253.17	4.89	131.71
	(217.03)	(468.98)	(453.63)	(538.97)	(734.11)
Post 2012	420.02*	687.61*			
	(231.15)	(352.63)			
Firm FEs		x	x	x	x
Year FEs			x	x	x
Year x Industry FEs				x	x
Controls					x
Observations	587	561	561	463	461
No. of Firms	190	164	164	143	143
Mean Dep. Var.	504.48	504.52	504.52	556.86	555.00

Notes: Results from estimating Equation 4 and including firms that have 20 to 80 employees in the year that they win a grant. Dependent variable is total R&D expenditures (£000*s*) but only for firms that report a positive R&D at least once, and then missing R&D values are considered zeros. Additional controls include (real) total assets and current liabilities. Standard errors are clustered by industry. Asterisks denote *p <0.10, **p <0.05, ***p <0.01.

Table C.6: Additional Tests for Selection and Placebo Tests

Outcome Variable:	R&D	R&D	R&D	R&D
	Proposal Manipulation		Pseudo-Thresholds	
	(1)	(2)	(3)	(4)
Treated * Post 2012	440.85**	457.86**	83.39	-63.89
	(201.79)	(186.41)	(241.84)	(330.44)
Treated	99.22	25.11	-102.72***	-3.97
	(345.34)	(356.75)	(36.51)	(15.29)
Firm FEs	x	x	x	x
Year FEs	x	x	x	x
Year x Industry FEs	x	x	x	x
Controls	x	x	x	x
Type of R&D FEs	x			
Proposed Cost Control		x		
Pseudo-Threshold 30			x	
Pseudo-Threshold 70				x
Observations	1,147	1,147	1,623	1,188
No. of Firms	386	386.	602	380
Mean Dep. Var.	248.90	248.90	192.66	301.73

Notes: Results from estimating Equation 4 and including firms that have 20 to 80 employees in the year that they win a grant. Dependent variable is total R&D expenditures (£000*s*) Asterisks denote *p <0.10, **p <0.05, ***p <0.01.

Table C.7: Pre-Policy Covariate Balance for Small Firms

Outcome Variable:	Tot. Assets (1)	Curr. Liab. (2)	SR Loans (3)	Oper. Profit (4)	Avail. Funds (5)	Liq. Ratio (6)
Treated	-0.92	-0.37	-1.31	0.35	0.62	0.06
	(2.37)	(3.01)	(3.21)	(0.65)	(0.61)	(0.82)
Year x Industry FEs	x	x	x	x	x	x
Observations	354	353	277	354	342	353
No. of Firms	174	174	144	174	168	174
Mean Dep. Var.	7.41	-4.23	-3.29	-0.97	-0.72	1.83

Notes: Results from estimating a regression discontinuity model, where treated is if the firm qualifies as a small firm under the Innovate UK rules in the year it wins a grant and the dependent variables are covariates. Sample includes firms with 20 to 80 employees. Monetary dependent variables are in GBP millions. The findings show that there is no statistically significant difference in these covariates around the small firm employee threshold. Asterisks denote *p <0.10, **p <0.05, ***p <0.01.

Table C.8: 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 C.9: Pre-Policy Covariate Balance for Larger Firms

	Means			Observations	
	<500	$\geq$ 500	Difference	< 500	$\geq$ 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. Conducting t-tests of differences in the means indicates that there are no statistically significant differences between firms just below and above the tax credit generosity threshold.

Table C.10: Pseudo Threshold Falsification Tests for 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 C.11: Results for Larger Firms When Using Lagged Employment

Employment year(s) used to define tax credit treatment	One Year Lag		Current + One Year Lag		Current + Two Year Lags	
	<500	$\geq$ 500	<500	$\geq$ 500	<500	$\geq$ 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*** (2.100)**		**-4.267** (1.787)**		**-4.819** (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 C.12: Robustness to Increasing Polynomial Flexibility for Larger Firms

Polynomial:	Linear		Quadratic		Cubic	
	<500	$\geq$ 500	<500	$\geq$ 500	<500	$\geq$ 500
	(1)	(2)	(3)	(4)	(5)	(6)
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 (baseline)	x	x				
Quadratic			x	x		
Cubic					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 running variable. 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.

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