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

Job Market Paper

Jacquelyn Pless*

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Abstract

Governments subsidize R&D through a mix of interdependent mechanisms, but subsidy interactions are not well understood. This paper provides the first quasi-experimental evaluation of how R&D subsidy interactions impact firm behavior. I use funding rules and policy changes in the UK to show that direct grants and tax credits for R&D are complements for small firms but substitutes for larger firms. An increase in tax credit rates substantially enhances the effect of grants on R&D expenditures for small firms. For larger firms, it cuts the positive effect of grants in half. I explore the mechanisms behind these findings and provide suggestive evidence that complementarity is consistent with easing financial constraints for small firms. Substitution by larger firms is most consistent with the subsidization of infra-marginal R&D expenditures. I rule out some alternative explanations. Subsidy interactions also impact the *types* of innovation efforts that emerge: with increases in both subsidies, small firms steer efforts increasingly towards developing new goods (i.e., horizontal innovations) as opposed to improving existing goods (i.e., vertical innovations). Accounting for subsidy interactions could substantially improve the effectiveness of public spending on R&D.

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

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1 Introduction

Fostering innovation and economic growth is one of the most pressing economic challenges. In an effort to drive innovative activity, most advanced countries offer subsidies for research and development (R&D), comprising hundreds of billions of dollars in public expenditures each year.[1] The economic case for government intervention is straight-forward: competitive markets undersupply innovative activity due to knowledge spillovers, as firms do not fully appropriate the benefits of their innovations (Nelson 1959; Arrow 1962).[2] Governments use a wide variety of instruments—such as direct grants and fiscal incentives—which they often layer on top of each other and frame as "complementary policies".[3] Yet while there is growing evidence documenting the effects of individual schemes on firm behavior and innovation outcomes, subsidy interdependencies that can undermine or enhance efficiency have been ignored. In fact, policy interactions are common in many economic settings, but there is limited, well-identified evidence of complementarity.

In the first quasi-experimental evaluation of R&D subsidy interactions, I test whether direct grants and tax credits for R&D are complements or substitutes in their effects on firms' R&D investment behavior. That is, how does the marginal effect of increasing one subsidy (grants) change with increases in the other subsidy (tax credits)? Different types of subsidies for R&D could be entirely interchangeable, but alternatively, they could serve distinct purposes for separate projects that may have technical complementarities. My empirical context is the UK, which offers the rare opportunity to examine multiple widely-used R&D support schemes that firms use simultaneously but which have funding rules that generate separate sources of exogenous variation in the cost and profitability of R&D. I match firms across several detailed datasets and implement two quasi-experimental research designs to study both small and large firms given the potential differences in innovation incentives, sensitivities to cash flow shocks, and types of innovations realized across the firm size distribution (Akcigit and Kerr 2018), with a focus on the intensive margin.[4]

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

[1] See the OECD Main Science and Technology Indicators for global spending on indirect and direct government funding of business R&D.

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

[3] For example, documentation from a U.S. House of Representatives hearing on innovation policy states: "Congress should consider complementing a lower capital gains rate for successful early-stage investments with a tax credit for investments in innovative small businesses" (U.S. Government, 2010). The terminology is common across policy fields. A search of the terms "complementary policies" in the online U.S. Government Publishing Office yields more than 20,000 results.

[4] The intensive margin refers to increases in R&D expenditures by firms that already invest in R&D, whereas the extensive margin refers to increases in R&D expenditures by firms that do not already invest in R&D. The R&D tax credit scheme in the UK primarily affects firm behavior and innovation outcomes on the intensive margin (Dechezleprêtre, Einiö, Martin, Nguyen and Van Reenen 2016), and thus this is the most relevant margin to study. I am also restricted by data limitations.

firms, I use a different sharp discontinuity (in the tax credit rate) to identify the effect of tax credits on R&D expenditures. I then estimate the impact of grant funding on each side of the tax credit rate threshold. Calculating the difference in the grant effect below and above the exogenous tax credit generosity threshold allows for a test of complementarity.

My results show that the subsidy schemes are complements for small firms but substitutes for larger firms on the intensive margin, and the effects are economically significant. For small firms, a 10 percentage point increase in the grant award rate has no effect statistically on R&D expenditures on its own. However, with substantial increases in tax credit rates, the grant effect becomes large and positive, such that R&D expenditures more than double. Expenditures on R&D increase by 142 percent on average. This positive, large, and statistically significant interaction effect indicates that the marginal effect of grant funding is enhanced substantially with a marginal increase in tax credits. The data provide no evidence that this positive interaction arises simply due to increasing returns to total subsidies—which may be the case if R&D expenditures are convex in total subsidies—but rather that the two subsidy types are complements for small firms.

For larger firms, the results are entirely flipped. I first estimate the impact of more generous tax credits alone using a standard regression discontinuity design. The tax credit policy that generates an exogenous decrease in the cost of investing in R&D for firms under a specific size threshold has a positive impact on R&D expenditures. The effect is large in magnitude, equating to an R&D price elasticity of 2.7. This is nearly identical to the estimate of the UK's tax credit policy effects in Dechezleprêtre et al. (2016), who use a similar identification strategy but different data and a different running variable to determine treatment status.

These estimates do not capture subsidy interdependence, though. Accounting for subsidy interactions demonstrates that—while higher tax credit rates have a positive impact independently—they also *dampen* the positive effect that direct grants have on R&D expenditures for these larger firms. The effect of direct grant funding on R&D expenditures on its own is also positive, but this positive effect of grants is significantly lower for firms that are just under the tax credit generosity threshold (and thus benefit from higher tax credit rates) relative to those that are just over it. The difference is substantial: increasing tax credit rates cuts the positive effect of grants in half. The negative, large, and statistically significant difference in the marginal effect of grant funding at the tax credit generosity threshold indicates that the two subsidies are substitutes.

I also examine the interaction effects on the *types* of innovation efforts and outcomes that firms make by linking the R&D expenditure data to innovation survey data. Understanding whether certain subsidy types are better suited for fostering different types of outcomes is useful for firms' innovation strategies and decision-making. It is also important for policy, as the composition of research may influence long-run economic growth (Akcigit and Kerr 2018; Akcigit, Hanley and Serrano-Velarde 2017a). I show that subsidy complementarity enhances small firms' efforts towards developing new goods and services (i.e., horizontal innovations) as opposed to improving existing goods and services (i.e., vertical innovations).[5] It also increases the probability that small firms

[5]This is consistent with corporate life cycle theory (Klepper 1996), if firm size is correlated with firm age.

produce new or significantly improved goods as opposed to processes.[6] If horizontal innovations are the stronger engine of economic growth, these findings suggest that subsidy complementarity for smaller firms may have an enhancing effect on long-run economic growth.[7]

What mechanisms can explain why these subsidies are complements for small firms and substitutes for larger firms? One plausible explanation of subsidy complementarity is it helps firms overcome financial constraints related to high fixed costs and indivisibilities. Investing in R&D may entail acquiring new equipment or even building an entirely new lab. Indivisible costs such as these can create barriers to undertaking or expanding projects if they are very large (Greenhalgh and Rogers 2010), and financially-constrained firms may require an upfront grant for such expenses rather than waiting for a tax credit that comes later. Consistent with this theory, I show that subsidy interactions enhance small firms' investments in expensive and indivisible R&D inputs such as advanced machinery and equipment as well as land and buildings. I also estimate the subsidy interaction effects on R&D expenditures for different subsets of firms to explore whether the complementarity is more significant for firms that may be more financially constrained. The point estimates are much larger for younger firms as well as those with higher current liabilities and fewer current assets.[8] Taken together, these findings suggest that the use of both subsidy types helps small firms overcome barriers associated with large, indivisible costs.

For larger firms, subsidization of infra-marginal expenditures (i.e., expenditures that would have been privately profitable even without additional subsidies) can explain why higher tax credit rates reduce the marginal effect of grants. Consider the following. If subsidies are used interchangeably, decision-making by larger firms is based upon total subsidies to help fund total R&D expenditures. An increase in the tax credit rate increases the proportion of total expenditures that is subsidized, decreasing the marginal return to both subsidy types due to diminishing returns. One implication of this—which may be useful evidence, if true, for the subsidization of infra-marginal expenditures as a mechanism that explains the results—is that public funds displace firm-financed expenditures (as opposed to expenditures financed by other entities). This can be tested. I show that all of the substitution occurs through a reduction of the firm's internally-financed R&D expenditures.

There are, of course, alternative explanations for subsidy complementarity and substitution. Many of these can be ruled out. For example, the effects found for small firms could be simply a function of R&D input relabelling, whereby firms deem non-R&D expenditures as R&D expenditures in order to reap larger subsidy benefits. I show that increases in R&D labor are not offset by decreases in non-R&D labor. Learning-by-doing and absorptive capacity may also explain complementarities, but these are more likely to characterize older and more experienced firms. Alternative explanations for subsidy substitution include inelastic supply of R&D inputs, relabelling of capital investments as non-capital investments, political capture, and information asymmetries. The

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

[7]This is based on the conclusions of Segerstrom (2000), who shows that R&D subsidies have positive effects on long-run economic growth if they increase the type of innovation that is the stronger engine of growth. See Section 6.

[8]Due to the small sample size, the standard errors for these estimates are large, but the magnitudes of the estimates are much higher for firms with these characteristics.

former two are not consistent with the data, and the latter two are unlikely to explain the results given the empirical setting.

This paper overcomes several identification challenges in order to evaluate R&D subsidy interactions. Selection bias is the most obvious concern: innovative firms are more likely to win grant competitions and receive tax credits. Funding agencies also may select projects based upon perceived potential for success. In the case of tax credits, another complication often faced in the literature is that firm-level variation is limited when tax rules apply to all firms, thus leaving variation to be determined by endogenous firm choices. Furthermore, public investments and policy changes are likely to coincide with unobserved factors that also influence innovation activities, such as where scientific opportunities are increasing (Lichtenberg, 2001). Disentangling the effects of different subsidies is complicated further by firms selecting into related policies in clusters and funding eligibility rules frequently aligning, making it difficult to attribute effects to one policy over the other. Using sources of exogenous variation that are distinct for direct subsidies and tax credits allows for these endogeneity concerns to be addressed.

This paper makes four main contributions. First, and most importantly, it establishes the complementarity and substitution relationships of different types of R&D subsidies for small and larger firms.[9] As such, it contributes to two distinct but related literatures evaluating R&D subsidy programs and fiscal incentives. Most recently, Howell (2017), Azoulay, Graff Zivin, Li and Sampat (2018), Bronzini and Iachini (2014), and Einiö (2014) provide quasi-experimental evidence that direct R&D subsidy programs have positive impacts on firm outcomes.[10] Guceri and Liu (forthcoming), Dechezleprêtre et al. (2016), and Bøler, Moxnes and Ulltveit-Moe (2015) conduct quasi-experimental evaluations of R&D tax credits.[11]

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

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

[10] Other studies on R&D grants include Lerner (2000), Wallsten (2000), Jacob and Lefgren (2010), Bronzini and Piselli (2016), and Takalo, Tanayama and Toivanen (2013). David, Hall and Toole (2000) survey earlier literature.

[11] Furthermore, Bloom, Griffith and van Reenen (2002), Wilson (2009), and Moretti and Wilson (2017) examine R&D tax incentives at the macro- or state-level. Bloom and van Reenen (2013) also use tax credit changes as instruments to study how the U.S. tax credits impact knowledge spillovers.

Roberts (2013) who focus on management practices.[12]

Third, this paper may be of interest to other fields of economics for which policy interactions are prevalent, such as in labor, development, health, and environmental economics.[13] Governments often implement an array of instruments to address the same externalities, and thus policy complementarities are of interest in many settings. However, evidence is typically limited due to the difficulty in finding separate sources of exogenous variation for multiple instruments.

Lastly, the results of this paper are important for policy. Accounting for complementarity and substitution between subsidy schemes in policy design could substantially improve the effectiveness of public spending on R&D. Innovation has long been recognized as a central driver of economic growth (Romer 1990; Aghion and Howitt 1992 1998). 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. Direct grants and tax credits are two of the most popular instruments that governments use to subsidize R&D, and studying their effectiveness and interactions is critical for optimal policy design. Complementarity of subsidies for small firms suggests that these firms are currently under-subsidized, whereas subsidy substitution suggests that increasing tax credits for larger firms is sub-optimal for firms that already receive grants.[14] Although the estimates in this paper are local to the empirical setting, as they are for any study of this kind, similar policy designs and interdependencies exist in many other contexts.

The remainder of this paper is organized as follows. Section 2 describes the key institutional features of the two main subsidy schemes studied here. Section 3 and Section 4 detail the data, empirical strategies, validity of research designs, and results for the small and large firm analyses, respectively. Section 5 examines the specific mechanisms that are consistent with the results and rules out some alternative explanations. Section 6 discusses policy and economic growth implications, and the paper concludes in Section 7.

2 Institutional Setting

This section discusses two public funding resources for private R&D in the UK and the institutional features used for identification in this paper: Innovate UK, which provides direct grants through competitions, and the R&D Tax Credit Scheme, which is available to all firms conducting R&D in the UK. Each program's rules for defining subsidy rates (i.e., the proportion of expenditures that are funded) induce quasi-experimental variation in the cost and profitability of investing in R&D. Descriptions of the data and methods are reserved for Sections 3 and 4, as they differ for small and

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

[13] 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).

[14] Many countries are increasing R&D tax credit rates for small firms, but some are also extending more beneficial rates to firms that are considered large for all other intents and purposes.

large firms, with additional details on data preparation provided in Appendix A.

2.1 Innovate UK: Direct Grants for R&D

Innovate UK, a non-departmental public body, is the UK's premier grant-awarding agency for the private sector. It has provided more than £1.8 billion in subsidies through grant competitions since 2007 with 500 million budgeted for the 2017/18 financial year (InnovateUK n.d.). The agency's main objective is to drive productivity and economic growth by providing funding support to private businesses (InnovateUK n.d.). Funding support is available to businesses across all sectors and firms in UK regions.

Innovate UK runs numerous funding competitions for grants each year. As part of the process, applicants are required to submit project cost and activity details. Awardees are subjected to finance checks and recipients must profile costs across the duration of funded projects. Eligibility requires that costs are incurred and paid between the project start and end dates, and claims are subject to independent audits, reducing incentives to relabel or incorrectly document spending.

I study firms that receive grants through Innovate UK in the small firm analysis. The main features of the program that I exploit are the funding generosity rules that define different subsidy rates based upon firm size. More generous proportions of eligible project costs are subsidized by the program for "small firms". Businesses are classified as micro/small, medium, or large based upon staff headcount and either turnover or balance sheet total, following the definitions set out by the European Commission.[15] Small firms are classified as those with fewer than 50 employees and either a maximum turnover or balance sheet total of €10m.

For most types of research, grants are ten percentage points more generous for firms just below the small firm threshold relative to firms just 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.

2.2 The UK's Tax Credit Scheme

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

[15] SMEs are defined in the EU recommendation 2003/361.

that the volume-based design offers is simplicity, and thus it is widely used by firms of all sizes.

The UK's R&D tax credit is particularly generous for SMEs: the rate of relief amounted to 150 percent of eligible expenses when it was first introduced, allowing a deduction of an additional 50 percent enhancement rate of qualifying R&D expenditures from taxable profits on top of the 100 percent deduction that applies to any expenditures. Enhanced losses can be surrendered for a payable tax credit if the SME does not earn profits, so all SMEs investing in R&D can benefit from the scheme in some way—even those that are liquidity constrained.[16] Large firms are eligible for a deduction rate of 130 percent from 2008 through 2016.

Since its inception, the deduction rate for SMEs has increased through policy changes several times up to 175 percent in 2008, 200 percent in 2011, and 225 percent in 2012. I focus on years after 2008 to avoid any complications around the financial crisis and examine the tax credit change in 2012 for the difference-in-discontinuities approach used to study small firms in Section 3.

There were several other changes made to the policy in 2008 that altered eligibility rules for R&D tax relief, which I use to identify the tax credit effect for larger firms. Before 2008, SMEs were defined as they were for all other intents and purposes in the UK, following the EU SME definition. In August 2008, however, the SME employment threshold increased from 250 to 500, the sales threshold from €50m to €100m, and the total asset threshold from €43m to €86m. Firms that were previously considered large firms can now qualify for the more generous R&D tax relief rates offered to SMEs. I use this new employment threshold for identification of the tax credit impact when studying larger firms in Section 4.

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

3.1 Data and Summary Statistics

Data sources and preparation.—I use four data sources to study small firms. First, Innovate UK's Transparency Database contains information on all grants given through the program since its inception. Second, Bureau van Dijk's Financial Analysis Made Easy (FAME) database provides balance sheet information for publicly listed firms in the UK. Third, since FAME does not detail the types of innovation investments that firms make or the outcomes that are achieved, I also enhance the data with the UK's Community Innovation Survey (CIS) and Business Enterprise Research and Development (BERD) databases, which are provided by the UK's Office of National Statistics in the UK Data Services Secure Lab.

The Innovate UK database includes grant details such as the total amount awarded, grant competition title and year, total project cost, legal status of firm, project status, and full firm location postcodes. It also includes unique company registration numbers (CRNs), which enable matching to other firm-level datasets such as FAME. The FAME dataset includes the primary

[16] On the other hand, loss-making large firms cannot claim a refundable tax credit, and the deduction rate is less generous (Finance Act, 2002).

outcome variable of interest—R&D expenditures—as well as other firm-level information required for determining firm size.

The CIS is a bi-annual survey of up to 16,000 enterprises covering information on innovation activities, such as the types of innovations that they pursue.[17] The BERD data provides further details on how firms allocate R&D expenditures. The CIS and BERD databases are held and protected by the UK's Office of National Statistics (ONS), which requires analysis to be conducted within the UK Data Services Secure Lab.[18] I obtained special permission to import the Transparency Database into the Secure Lab environment so that it could be matched the BERD and CIS data.

I use employment as the running variable to determine firm size. Using employment, rather than total assets or turnover, allows for consistency in the running variable throughout the paper.[19] Since grant awards are determined when the project proposal is submitted and reviewed, I use the firm's employment from the year before it receives a grant to determine treatment status.

Details on how each dataset is prepared and merged can be found in Appendix A. I match 88 percent of the 16,167 observations from the final Innovate UK database to FAME over the period of 2005 through 2016. There are no meaningful differences between the unmatched and matched firms. Most of those that did not match either had missing or incorrectly specified CRNs in the Innovate UK database.

I restrict the data further in three main ways. First, I limit the sample to grants given in 2008 or later. Including outcomes from years prior to the 2008 financial crisis may bias the results if firms that survived differ systematically from those that did not in ways that impact innovation effort or capacity. For example, firms that survived the crisis may be particularly innovative and thus may have higher innovation outcomes compared to firms observed before the crisis. On the other hand, innovation outcome effects from grants may differ before the crisis if firms were more financially constrained, which has been shown to impact firm responsiveness to grants (Howell 2017).[20]

Second, to ensure the results are not driven by outliers, I trim the sample by dropping the top and bottom 5 percent of the R&D investment distribution. This addresses the concern that innovation investments vary significantly across firms and can be highly volatile over time (Bronzini and Iachini 2014).[21] Third, as discussed in Section 3.2, I limit the data to varying windows around the small firm employment threshold, showing robustness to a range of alternatives.

Descriptive statistics.—Table 1 presents descriptive statistics of the final prepared datasets, covering firm-year observations when firms receive grants from 2008 through 2017. All nominal financial variables are converted to 2010 real prices using the World Bank's Consumer Price Index for the

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

[18]It also required training to be an accredited researcher, and an approved project proposal to use the data.

[19]The total assets variable is not in the dataset used to study other innovation outcomes with the UK's Community Innovation Survey or in the datasets available for studying larger firms. Turnover is available but less complete than employment. Using one running variable does not violate any assumptions associated with RDD.

[20]My data also do not cover R&D expenditures prior to 2008 due to FAME database subscription limitations.

[21]The results are robust to not dropping any outliers (see Section 3.5).

UK. The full sample includes 11,813 grant awards given from 2008 through 2017 to 7,988 unique firms.[22] I use three sub-samples of firms of varying window sizes around the grant generosity threshold based on the firm's employment level: fewer than 100 employees (wide window), 10 to 90 employees (midrange window), and 20 to 80 employees (narrow window).

The sample sizes become quite small once matched to the R&D data, since not all firms report R&D expenditures.[23] In the wide window sample, for example, there is R&D expenditure data for 197 of the 1,160 observations, with 95 observations below the small firm threshold and 102 observations above it. In the narrowest window used, there is R&D expenditure data for 124 of the 625 observations, with 56 observations below the small firm employment threshold and 68 above it. Although the use of large, detailed datasets offers the benefit of providing enough data to implement a diff-in-disc research design, matching to the R&D expenditure data and limiting the sample around the threshold reduces the sample size substantially. Nonetheless, I show that the results are robust to narrow and wide windows around the cutoff. They are also robust to numerous other specification and falsification tests (see Section 3.5), and the results are replicable using different data on R&D expenditures (see Section 4).

Table 1: Innovate UK Grant Award and Outcome Variables, Descriptive Statistics

	Full Sample	Wide Window (< 100 Employees)	Midrange Window (10 to 90 Employees)	Narrow Window (20 to 80 Employees)
Panel A: Grant Awards				
No. of Unique Grants	11,813	1,160	882	625
No. of Unique Firms	7,988	834	639	466
Grant Amount (£000s)	£304.08	£708.33	£758.92	£748.22
	(£2,692)	(£5,968)	(£6,556)	(£6,926)
Total Project Cost Funded (%)	65.3%	58.0%	57.4%	57.0%
	(23.5%)	(22.8%)	(21.9%)	(22.3%)
Panel B: Outcome				
R&D Expenditures (£000s)	£7,598.13	£1,284.54	£1,409.98	£1,458.59
	(£17,428)	(£1,907)	(£1,994)	(£2,029)
No. of Observations	818	197	156	124

Notes: Descriptive statistics for firms in Innovate UK and Bureau van Dijk's FAME final prepared datasets used in the small firms analysis. Only firm-year observations when grants are received from 2008 to 2017 are included.

3.2 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 (e.g., Grembi, Nannicini and Troiano (2016)). The approach uses two sources of exogenous variation in R&D investment costs created by the funding rules and policy changes that are different for each subsidy type: 1) a discontinuity

[22] Some firms receive multiple grants over this time period.

[23] I discuss the potential issues that this introduces and provide robustness checks to rule them out in Section 3.5.

in grant funding generosity based upon firm size (employment), and 2) an increase in the tax credit generosity that occurs in 2012. The basic idea is to estimate the impact of increased grant generosity using a standard RDD, and to then estimate how that discontinuity changes when tax credit rates increase to capture the difference in the discontinuity.

Focusing first only on the average impact of increased grant generosity induced by the Innovate UK funding rules at the small firm size threshold, I begin with the sharp RDD setup. The outcome variable is a function of the running variable (employment), which defines firms as small for grant generosity purposes.[24] The average treatment effect of increased grant generosity is given by the estimated value of the discontinuity at the small firm threshold as follows:

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

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

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

My main objective, however, is to test whether grants and tax credits are complements or substitutes. To do this, I combine this sharp RDD identifying the grant effect with before/after variation generated by the tax credit rate increase in 2012 to estimate how the (grant generosity) discontinuity changes (with increased tax credit rates). The intuition is that the discontinuity will be larger after tax credit rates increase if tax credits and grants are complements. It will remain unchanged if they are independent and it will decrease if they are substitutes. I assume all firms in the sample apply for and receive the R&D tax credit, since I do not observe this in the data.[25] The effects estimated for the tax credit increase capture the intent-to-treat (ITT).

I implement this diff-in-disc research design by estimating the following model:

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

[24] Using just a single running variable may reduce the efficiency of the estimates but it does not violate the assumptions for RDD.

[25] This is a reasonable assumption for these firms—the tax credit has been in place for a number of years. It is large and salient, and conversations even with very small firms suggest that they not only know of it but they plan for it in their budgets.

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

Although it is common in RDD analyses to control for higher-degree polynomials of the forcing variable, recent work has shown that researchers should use only local linear or quadratic polynomials (Gelman and Imbens 2017). Higher-order polynomial models may be imprecisely estimated when the sample size is small (Lee and Lemieux 2010), as it is here, so I model the forcing variable linearly throughout most of the analyses. I show that the results are robust to higher order polynomial controls in Section 3.5. Furthermore, rather than estimating the difference-in-discontinuities for both the 2011 and 2012 tax credit rate changes, I consider just a single posttreatment period (after 2012) due to the small sample size.

3.3 Validity of Research Design

The primary concern regarding the validity of the diff-in-disc research design is related to the cross-sectional variation: the firm size cutoff determining grant rates must be exogenous, and RDD is only suitable if firms cannot perfectly manipulate the running variable (Lee 2008). In this setting, manipulation is possible if particularly savvy firms purposely maintain firm size just below the threshold in order to take advantage of more generous grant offers. Manipulation may also occur if there are other policies that create substantial benefits for firms at this exact threshold.[26]

This would be problematic for identifying the grant effect in an RDD if savvy firms manipulate firm size and those just under the grant generosity threshold differ from those just above the threshold in systematic ways that are unobservable and correlated with the outcome. Furthermore, using the time-series variation for identifying the tax credit effect on the discontinuity (i.e., the interaction effect) will be biased if there are other policy changes in the same year that *differentially* affect firms just below and above the small firm size grant generosity threshold.

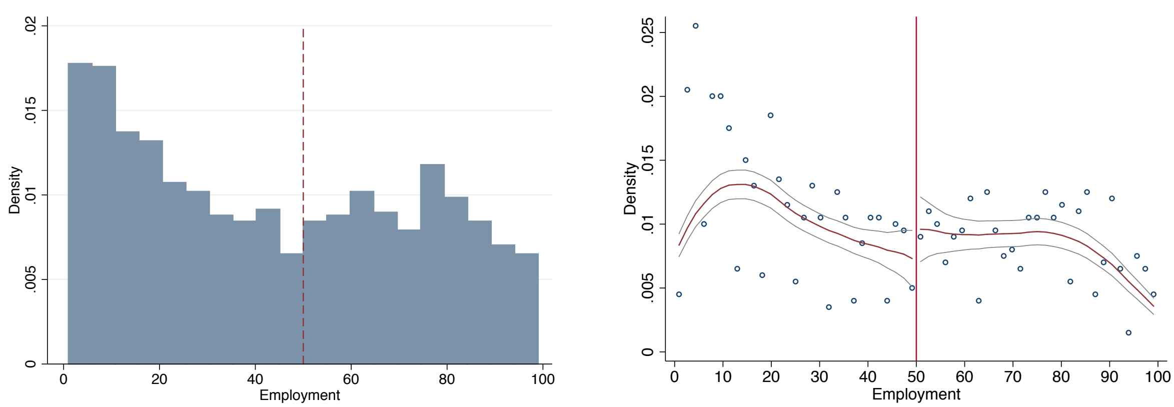
I employ five empirical tests of randomization at the small firm employment threshold to provide confidence that the continuity assumption is satisfied and that the distribution of predetermined variables is smooth around the cutoff. First, in Figure 1, Panel A, I inspect whether there is an increase in the density of firms just under the small firm threshold, as would be expected if firms manipulate the running variable in response to the funding rules (or any other policy generating

[26] For instance, in France, many labor laws start to bind on firms with 50 or more employees, and thus significant bunching can be found just under the small firm threshold (Garicano, Lelarge and Van Reenen 2016). In Appendix Table B.3, I provide details on a sample of UK policies that I reviewed to confirm this is not the case here in addition to the formal empirical tests.

different incentives for firms just below this threshold). I find no visual evidence of a spike in the density function, or "bunching", around the cutoff. Second, I conduct a McCrary density test for firms based upon employment (Figure 1, Panel B). The discontinuity estimate (log difference in density height at the threshold) is 0.298 with a standard error of 0.227, suggesting that there is no statistically distinguishable discontinuity in the firm size distribution at the threshold.

Third, treated and untreated firms around the threshold should be similar in observed characteristics as a consequence of randomization (Lee 2008). I verify this by showing that there are no statistically significant differences in treated and untreated firms' mean covariates around the cutoff point (see Table 2).[27] Using the wide window subsample, I test for differences in total assets, current liabilities, total proposed project costs, and the average grant amount for the competition in which a firm receives a grant. The null hypothesis that means are the same cannot be rejected in any case when conducting t-tests.

Figure 1: Evidence of No Manipulation at the Small Firm Employment Threshold



(a) Histogram Based Upon Employment

(b) McCrary Density Test Based Upon Employment

Note: Histogram and McCrary test for discontinuity in distribution density of total employment at the small firm employment threshold. Sample includes firms with fewer than 100 employees. Log difference in density height of 0.298 with a standard error of 0.227.

Fourth, I reinforce the conclusion that there are no statistical differences in these covariates at the threshold by estimating the RDD model of Equation 1 with these covariates as dependent variables. The results are presented in Appendix Table B.1. The discontinuity is statistically zero in all cases. Lastly, I estimate the full diff-in-disc model of Equation 2 with these covariates as dependent variables to provide confidence that they do not change *differentially* at the cutoff at the same time that tax credit rates change. If there is a difference in the discontinuity, there may

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

Table 2: Covariate Balance Around Small Firm Employment Threshold

	Means			Observations	
	<50	≥50	Difference	<50	≥50
Total assets (£ms)	£19.22	£15.63	-£3.59	658	500
Current liabilities (£ms)	£10.58	£8.18	-£2.40	648	498
Total proposed project costs (£000s)	£1,081.41	£733.73	-£347.68	660	500
Average Grant Amount in Competition (£000s)	£297.24	£209.21	-£88.03	660	500

Notes: Includes Innovate UK and FAME data for final samples used in difference-in-discontinuities regressions of firms with less than 100 employees. Only firm-year observations when grants are received between 2008 and 2017 are included. Financial variables are converted to real 2010 GBP. Table shows covariate balance between treated and untreated firms around small firm employment threshold. There are no statistically significant differences between covariate means, providing confidence in "randomization" of the grant generosity threshold.

be some other policy change in the same year that differentially affects firms just below and above the cutoff, which could confound the results. The diff-in-disc estimate is statistically zero in all cases (see Appendix Table B.2).

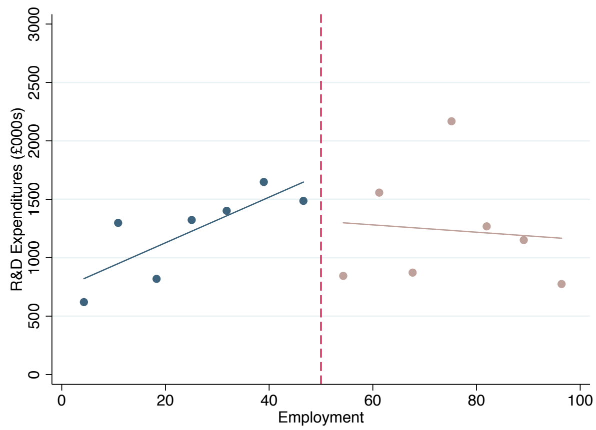
Taken together, these five tests provide confidence that firms do not manipulate total assets around the small firm threshold and that firms below and above the cutoff are similar. The cutoff for increased grant generosity can be interpreted as being as good as random, validating the cross-sectional RD component of the diff-in-disc research design. The last test also provides confidence that no other policy changes that may have occurred in 2012—when tax credit rates increased—differentially affected firms just below and above the grant generosity threshold.

I also conduct a thorough investigation of UK policies to ensure that there are no other schemes that generate benefits to small firms defined precisely as they are by Innovate UK. Fortunately, while the UK tends to offer special benefits and fiscal incentives to small- and medium-sized firms (SMEs), such policies and programs typically are not specific to small firms. Firms above the small firm threshold—up to the medium-sized firm threshold—are also eligible. When there are benefits specifically for smaller firms, the thresholds and definitions differ relative to the ones set by Innovate UK. This provides further reassurance that there are no confounding policies generating different incentives for firms just below the grant generosity threshold that would affect R&D investments. It also follows that there are no other policy changes that would affect firms differentially above and below the threshold in 2012, since such a threshold does not exist for other policies.

3.4 Main Results

Average Grant Effect.—Before examining subsidy interactions and results from the full diff-in-disc model, I begin with an analysis of the average effect of increased grant generosity over the entire time period of the sample. Figure 2 plots average R&D expenditures against increasing levels of employment for the years 2008 through 2017. To construct Figure 2, I assign firms to evenly-sized groups based upon employment and compute the mean R&D expenditures for observations within each group. I plot mean R&D expenditures against employment, superimposing a best-fit line on the points as a visual aid and allowing for the slope of the line to differ on each side of the grant generosity threshold.

Figure 2: Average Impact of Increased Grant Generosity on Firm R&D Expenditures



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

Figure 2 illustrates that R&D expenditures appear to increase in employment for firms receiving more generous grants on average, whereas there is no clear relationship above the threshold. It does not appear as though there is a jump at the discontinuity, but rather a kink, if anything.

Results from estimating this effect in the RDD model of Equation 1 are consistent with the graphical analysis (see Table 3). There is no statistically significant discontinuity in R&D expenditures at the cutoff. When using the wide window sample (Column 1, Table 3), the funding rule appears to induce a positive kink for firms receiving more generous grants, so that the slope of R&D investments as a function of employment increases. However, this is just barely statistically significant, and the estimates are statistically zero once narrowing the window around the threshold. The diff-in-disc estimator is statistically zero in all cases.

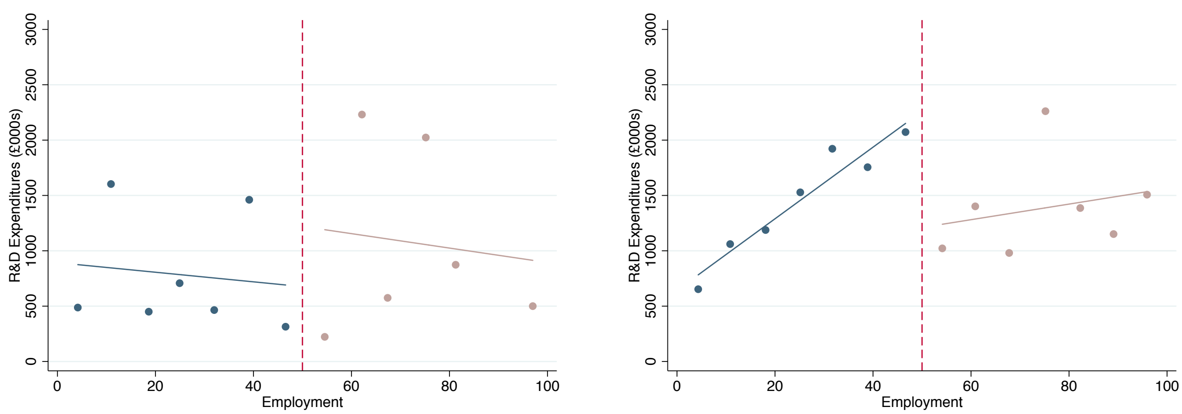
Policy Interaction Effects.—I now turn to the primary results capturing the R&D subsidy interactions, beginning with a graphical analysis. Figure 3 plots average R&D expenditures for evenly-spaced groups of firms below and above the grant generosity threshold, but separately for the period before the tax credit increase (2008-12) in Panel A and after (2013-17) in Panel B. Illustrating this heterogeneity tells a very different story relative to Figure 2. Higher grant rates for small firms just below the employment threshold appears to have no impact on R&D expenditures before 2012. However, after the 2012 tax credit rate increase, R&D expenditures increase substantially at the grant generosity threshold. This suggests that the increase in grant generosity had no effect on R&D expenditures without the additional increase in tax credit rates, but higher grant awards have positive and large effects once combined with a substantial tax credit rate hike.

Table 3: Impact of Increased Grant Generosity on R&D Expenditures, Small Firms

	Wide Window (< 100 Empl.) (1)	Midrange Window (10 to 90 Empl.) (2)	Narrow Window (20 to 80 Empl.) (3)
1[employment < 50]	365.94	181.81	1162.21
	(513.20)	(564.05)	(1134.33)
Employment * 1[employment < 50]	24.28*	-0.94	-40.16
	(12.18)	(27.15)	(55.41)
Sample mean for dependent variable	£1,283.54	£1,408.98	£1,458.59
No. of Observations	197	156	124

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

Figure 3: Impact of Policy Interactions on R&D Expenditures



(a) Before Tax Credit Increase

(b) After Tax Credit Increase

Note: Data points represent average R&D expenditures for evenly-spaced bins of firms receiving Innovate UK grants with fewer than 100 employees before (Panel A) and after (Panel B) the tax credit rate increase that occurs in 2012. The y-axis measures average R&D expenditures. The running variable is employment and on the x-axis.

Results from estimating the diff-in-disc model of Equation 2 confirm that the grant effect on its own is statistically zero, but the interaction effect is positive, large, and statistically significant (see Table 4). These results imply that the two subsidy types are complements for these small firms. Columns 1 to 3 present the results when using wide and more restricted sampling windows around the grant generosity threshold. I also include additional control variables for preciseness: firm age, distance to London, total grant funding awarded to the firm's competition in which it received a grant, and total grant funding awarded in the year. When considering the most conservative case (Column 2), the results indicate that the increase of both grant and tax credit rates enhance R&D expenditures by about £2m on average. This is a 142 percent increase relative to average R&D expenditures in the sample.

Table 4: Diff-in-Disc Results: Subsidy Interaction Effect on R&D Expenditures, Small Firms

	(1)	(2)	(3)
	Wide Window (< 100 Empl.)	Midrange Window (10 to 90 Empl.)	Narrow Window (20 to 80 Empl.)
1[year = post 2012] *1[employment < 50]	2254.32*	2001.58**	2814.91*
	(1143.42)	(944.65)	(1515.93)
1[year = post 2012] *1[employment < 50] *employment	23.87	87.05	27.55
	(28.82)	(57.78)	(62.68)
1[employment < 50]	-1251.91	-1177.35	-926.25
	(897.99)	(783.50)	(888.32)
Sample mean for dependent variable	£1,283.54	£1,408.98	£1,458.59
No. of Observations	197	156	124

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

3.5 Robustness of Results

I conduct a number of robustness checks to ensure that the results hold under different modelling assumptions and when addressing concerns with the data. I start with a falsification test in which I set artificial cutoffs in the running variable and test whether R&D expenditures are continuous across pseudo-thresholds. The outcome should be smooth, since policies do not alter the cost of investing in R&D at these arbitrary thresholds. Statistically significant discontinuities would suggest that the main results are simply an artifact of functional form assumptions. Table 5 presents results when setting three different random cutoffs, using both wide and narrow windows around the thresholds. No statistically significant differences in the discontinuities are detected.

An additional concern is that there is a low reporting rate for R&D expenditures in the FAME database. There are two potential explanations for this. First, it could be that small firms do not

Table 5: Diff-in-Disc Pseudo-Threshold Falsification Tests, Small Firms

	(1) Wide Window (+/- 70 Employees)	(2) Midrange Window (+/- 40 Employees)
A. Employment Threshold of 30		
1[year = post 2012] * 1[employ < 30]	-8.29	-1187.24
	(862.62)	(859.08)
No. of Observations	197	132
B. Employment Threshold of 70		
1[year = post 2012] * 1[employ < 70]	-115.31	–363.85
	(789.53)	(763.89)
No. of Observations	244	152
C. Employment Threshold of 90		
1[year = post 2012] * 1[employ < 90]	-3304.5	-2206.14
	(2217.42)	(1316.36)
No. of Observations	237	139

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

report these figures because they are not required to do so. Expenditures on R&D are reported by all publicly listed companies, but otherwise, firms are only required to report a certain sub-set of the financial variables in FAME. This could introduce bias in the cross-sectional component of the research design that identifies the grant effect if data coverage is different below and above the small firm threshold. However, this is not consistent with the data. The low coverage is similar for firms just below and above the threshold.

On the other hand, the data coverage improves significantly over time, indicating that the main threat to identification is related to the time variation component of the research design. One potential explanation is that firms report more frequently as the tax credit rate increases and it is more beneficial for the firm to reap the subsidy benefits. However, the UK's tax credit had already been in place for more than a decade before the tax credit rate changes, and the biggest change to its generosity happened in 2008 as opposed to 2012. The improved data coverage over time is more likely due to changes in Bureau van Dijk's data collection practices.[28]

Improved data coverage in later years could complicate the interpretation of the main diff-in-disc result if estimating no effect in early years is simply due to a small sample size. To ensure that this is not the case, I carry out a falsification test for the tax credit rate change timing by imposing artificial tax credit changes in later years, when the data are richest. The results are presented

[28] I am awaiting confirmation of this, but conversations regarding this data have indicated that the company has likely developed new partners over time that provide the data.

in Appendix Table B.4 when setting pseudo-tax credit change years as 2013 and 2014, and using different sub-samples of data around the grant generosity threshold. There are no statistically significant effects, suggesting that the main results can be attributed to the tax credit change as opposed to better data coverage in later years.

I conduct several other robustness checks and provide the findings in Appendix Table B.5. The main diff-in-disc results are robust to trimming the sample differently by either dropping fewer outliers (Column 1) or no outliers (Column 2), as well as when using quadratic polynomial controls (Column 3) or cubic polynomial controls (Column 4).

3.6 Interpreting the Results as Subsidy Complementarity

One interpretation of the large, positive interaction effect between direct grants and tax credits is that these subsidy types are complements. Increasing the tax credit rate greatly enhances the marginal effect of direct grants, and such complementarity gives rise to increasing returns. Another plausible interpretation is that the subsidies are substitutes but there are increasing returns to *total subsidies*. That is, small firms increasingly benefit from more subsidy funds regardless of source as opposed to benefitting from the combination of the two subsidy types.

To test this, I examine whether small firms' R&D expenditures are convex or concave in the total subsidies received. Convexity (concavity) of R&D expenditures in total subsidies would imply increasing (decreasing) returns to total subsidies. I calculate the implied tax credit amount that small firms receive based upon the tax credit rate and corporate tax rate each year and add this to the grant amount received to find each firm's total subsidies. Figure 4 plots average R&D expenditures against average total R&D subsidies for groups of firms. In Panels A and B, the full sample of small firms receiving grants is used, and Panels C and D are winsorized to omit the bottom and top 5% of the total subsidies distribution. Firms are grouped into 10 bins in Panels A and C plot and 30 bins in Panels B and D.

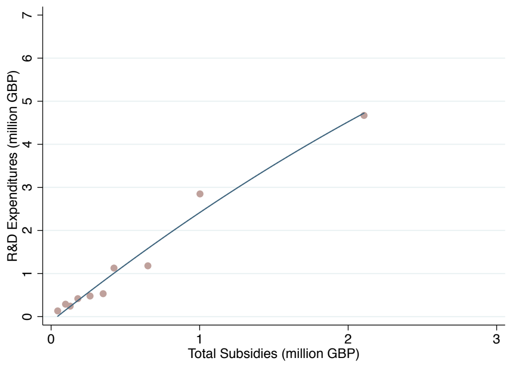
The plots of Figure 4 provide no indication that small firms' R&D expenditures are convex in total R&D subsidies. If anything, they are (very) slightly concave in all cases, although the coefficient on the total subsidies squared term is not statistically significant. This non-convexity suggests that the primary results of a positive interaction between direct grants and tax credits for small firms is *not* explained by increasing returns to total subsidies but rather a complementarity between the two subsidy types.

4 Large Firms: Evidence from a Regression Discontinuity

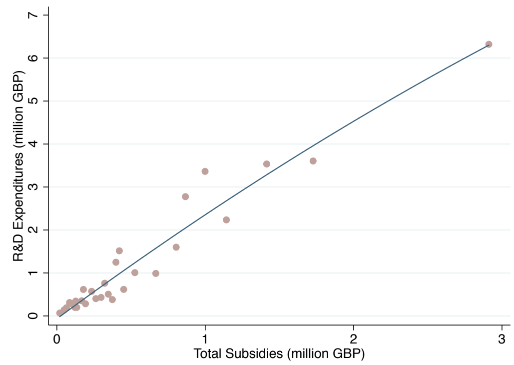
4.1 Data

The main data sources for studying larger firms include the UK's Business Enterprise Research and Development (BERD) and Business Structure Database (BSD) collected by the Office of National

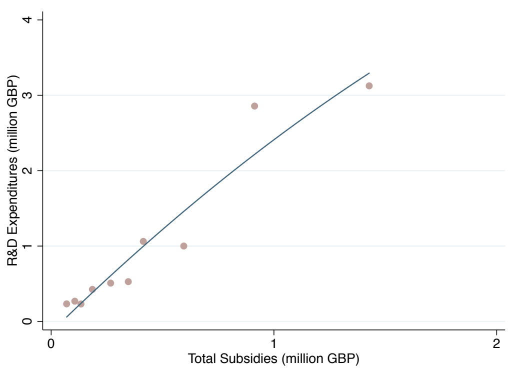
Figure 4: Evidence of No Increasing Returns in Total Subsidies



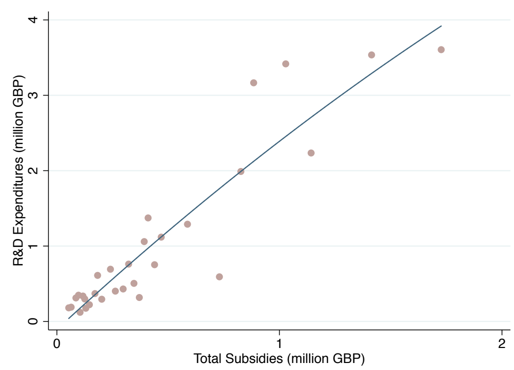
(a) Full Sample, Large Bins



(b) Full Sample, Small Bins



(c) Winsorized Sample, Large Bins



(d) Winsorized Sample, Small Bins

Note: Figures plot R&D expenditures as a function of total subsidies (direct grants and an implied tax credit amount) for small firms. Each point represents the average R&D expenditures for a group of firms. There are 10 bins of firms in Panels A and C and 30 bins of firms in Panels B and D. The full sample of small firms is used in Panels A and B and outliers are dropped in Panels C and D.

Statistics (ONS). Different datasets than those used in Section 3 are required because there are insufficient observations for larger firms in the Innovate UK data once merged with FAME. I augment the BERD and BSD data with calculations of the driving travel distance (in kilometers and time) between each enterprise and the central grant-funding agency in the UK (for the IV construction described below). A full discussion of the data sources and matching procedures can be found in Appendix A.

The BERD dataset provides information on R&D expenditures and the sources of funds supporting those expenditures. I proxy for "direct subsidies" with the proportion of R&D expenditures that is funded by the central government. These include grants, such as those allocated through innovation funding competitions, but also other direct support mechanisms. Importantly, the variable does not capture indirect funding received through tax credits. I use the Business Structure Database (BSD) to gather additional information that is required for determining treatment status in the RDD component of this analysis (see Appendix A for details). Although BERD reports firm size, these figures capture firm size at the reporting unit level, whereas tax credit rates are determined by firm size at the enterprise group level. The BSD provides enterprise group level employment information.

Appendix Table B.8 provides summary statistics of the BERD data for larger firms. The main feature to highlight is that a much smaller proportion of R&D is funded by direct subsidies for these larger firms compared to small firms. This aligns with the UK's policy goals towards focusing on supporting small firms with grants for innovation activities. The data are described further in Section 4.3 when confirming the research design validity.

Corroborating Small Firm Results.—An obvious concern with using different data to study larger firms is that conclusions drawn from the analysis could be an artefact of the data itself rather than how firms respond to incentives. To ensure that this is not the case, I begin by corroborating the small firm results with these data. There are drawbacks to using these datasets for the small firms' main analysis, since not all small firms within the economy are surveyed in BERD. The data owners interpolate missing values for small firms and identifying which observations have interpolated versus real data is not clear in some years. Nonetheless, corroborating the small firms' results with these data can provide confidence that differences in findings for larger firms are not driven by differences in the data.

Appendix Table B.6, Panel A provides the results from estimating the diff-in-disc model of Equation 2 (see Appendix A for the data matching required to do this), which are consistent with those found in Section 3. The diff-in-disc estimate for the subsidy interaction effect on R&D expenditures is positive, large, and statistically significant. One exception is that statistical significance is lost in the narrowest sub-sample of firms, but the estimate remains positive and large in magnitude. In the most conservative case, average R&D expenditures increase by 235 percent with increases in both subsidy types. Appendix Table B.7 provides falsification tests, imposing two pseudo-thresholds for grant generosity treatment status. Again, there are no statistical differences across varying subsets of data, providing confidence in the results and research design.

One benefit of using this data is that it provides more detail on the financing source of R&D expenditures. As one final test of how subsidy interactions affect small firms' R&D expenditures and innovation efforts, I estimate the diff-in-disc model for only firm-financed R&D (i.e., total R&D expenditures minus expenditures funded by the central government). This confirms that subsidy interactions have positive additionality effects on firms' own innovation investments beyond the subsidy amount. Appendix Table B.6, Panel B reports these results, which use internal finance (Column 1) and external private finance (Column 2) as dependent variables. Internal finance is the firm's expenditures on performing R&D funded by the firm's own funds as well as subsidiaries or the parent company. External private finance refers to R&D expenditures funded by private businesses in the UK and other non-governmental organizations. The results indicate that there is a strong, positive impact on internal finance but not external private finance.

4.2 Research Design

To study the impact of subsidy interactions for larger firms, I use a different discontinuity that creates exogenous variation in the generosity of the tax credit based upon a firm's size and estimate the effect of direct grants on each side of this discontinuity to capture the interaction.[29] Firms with fewer than 500 employees are eligible for a much more generous tax credit rate than those with more than 500 employees. I estimate the impact of *direct subsidies* on R&D expenditures separately on each side of this tax credit threshold. This allows for a test of whether the grant effect differs on each side of the tax credit generosity threshold. If the subsidies are complements, the grant effect should be higher for firms below the tax credit threshold, as these firms benefit from more generous tax credits. The grant effect should be lower for firms below the tax credit rate threshold if the subsidies are substitutes.

Of course, grant funding is endogenous for the many reasons discussed in the introduction: unobservable information influences the firm's ability to propose R&D projects, win grant competitions, and obtain funds. This would typically call for an instrumental variables approach to estimating the grant effect. However, the main objective here is to focus on the *interaction* of grant funding with tax credits as opposed to the scale of the grant effect itself. This subsidy interaction can be recovered by measuring the difference in the grant effect around the exogenously-determined tax credit threshold. As long as the endogeneity bias operates in the same direction and with a similar magnitude for firms just below and just above the tax credit rate threshold, using OLS is sufficient for estimating the interaction effect. I therefore combine the RDD with an OLS approach in the main analysis.

4.3 Validity of Regression Discontinuity Design

Section 2.2 describes the main policy feature that I exploit in the RDD. That is, firms with fewer than 500 employees receive more generous tax credits than those with 500 employees or more,

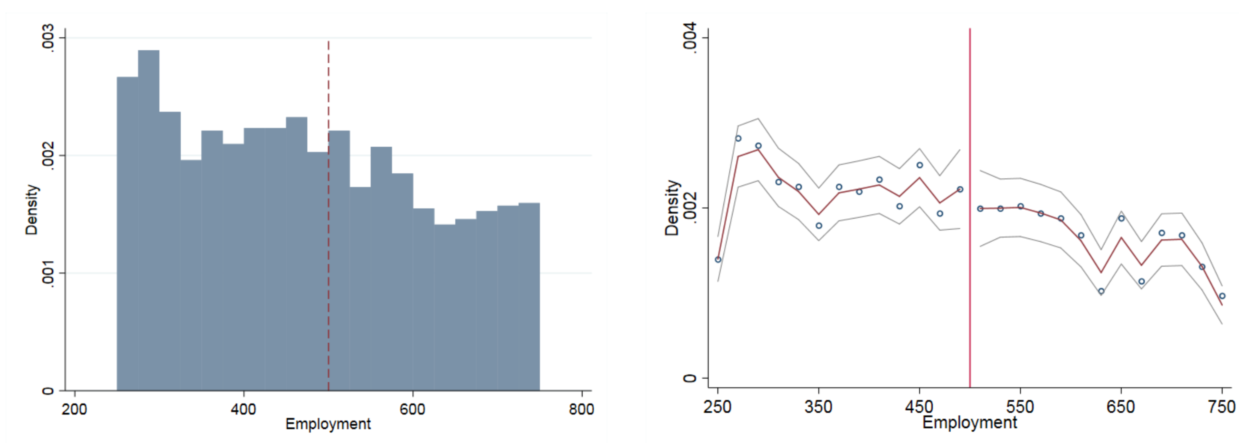
[29]There are no sources of exogenous variation in grant rates for larger firms as there are for small firms, so another diff-in-disc analysis is not feasible.

as they are considered SMEs for the purposes of the R&D tax credit. This employment cutoff generates a sharp discontinuity in the cost of investing in R&D for these relatively larger firms. The exclusion restriction is satisfied since the thresholds are at least double those of other policies that generate different innovation incentives and benefits that may affect firm behavior, which are typically set at the standard SME thresholds (250 employees). It is worth noting that although these firms are considered SMEs for tax credit purposes, this analysis effectively studies larger firms, since they are "large" by all other UK and EU definitions. They do not include the largest firms within the economy, though.

There are no other policies or programs that define firm size thresholds aligning with these that would confound estimating a LATE around the running variable cutoffs. The SME threshold definitions were doubled strictly for the purposes of the R&D tax credit, whereas they remained at their original cutoffs for all other intents and purposes. Nonetheless, to provide further confidence in the validity of the RDD, I conduct three empirical tests.

I start by checking whether the running variable—employment—is manipulated around the tax credit generosity cutoff of 500 employees. Bunching just under the threshold would suggest that firms are able to manipulate firm size to take advantage of the tax credit benefits, and savvy firms exhibiting this behavior may differ systematically from those just above the threshold, confounding a comparison of the two groups of firms. Figure 5 presents two tests for this type of manipulation. Visual inspection of the histogram in Panel A indicates that there is no obvious increase in the density of firms just below the cutoff, and the results from the McCrary test plotted in Panel B confirm that this is the case. The log-difference is not statistically significant at the threshold.

Figure 5: Evidence of No Manipulation at the Tax Credit Generosity Employment Threshold



(a) Histogram Based Upon Employment

(b) McCrary Density Test Based Upon Employment

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

Third, I test for continuity in observable covariates around the threshold in pre-policy years to provide confidence that the cutoff was randomly selected. Table 6 presents results when testing for statistical differences using t-tests on covariate means around the threshold in years prior to the implementation of the new tax credit generosity threshold (2000 to 2007). There are no statistical differences in variables such as turnover, direct subsidy levels, expenditures on different types of R&D, suggesting firms just below and above the threshold in pre-policy years are similar. There are also no statistical differences in the main outcome variable of interest—R&D expenditures. Taken together, these tests provide confidence that the tax credit generosity threshold can be interpreted as randomly assigned.

Table 6: Pre-Policy Covariate Balance Around Tax Credit Generosity Threshold, Larger Firms

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

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

Estimation of subsidy interaction.—I estimate the effect of direct subsidies on firm R&D expenditures separately on each side of the tax credit generosity threshold to capture the subsidy interaction. If the subsidies are complements (substitutes), the marginal effect of grants should be higher (lower) under the tax credit generosity threshold used in the RDD. The primary outcome variable of interest, Y_{it}, is R&D expenditures for firm i in year t. I estimate the following model:

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

where G_{it} is firm i's direct subsidy funding amount received in year t, and γ_t are year fixed effects to control for R&D expenditure trends within the economy over time. The specification also controls for time-invariant mean differences in R&D effort with δ_b business structure fixed effects and η_p product group fixed effects, and $\mathbf{X}_{it}$ includes additional controls for observable firm characteristics (such as age and employment).[30] Standard errors are clustered by industry, defined as the first two digits of the firm's SIC.

To estimate the subsidy interaction, I test whether the grant effect for firms just under the R&D tax credit generosity threshold is statistically different than the effect for firms just above the cutoff. A common approach to estimating treatment effect heterogeneity is to interact the

[30] Business structure refers to whether the firm is set up as a partnership or corporation.

treatment with other observables, however this severely over-rejects under model misspecification, even when data are limited to narrow windows around the running variable cutoff (Hsu and Shen 2016). To avoid this, I estimate Equation 3 separately on each side of the threshold and test whether the coefficients for the grant effect are statistically different, while still limiting the data to include only firms within a narrow window around the tax credit threshold.

An alternative instrumental variables estimation strategy.—As discussed, OLS is sufficient for estimating the subsidy interaction effect if the endogeneity of grant funding is similar just below and above the tax credit rate threshold. Nonetheless, using an instrumental variable (IV) strategy can provide insight into whether this holds. I propose an IV that uses variation in grant funding levels that arises due to the interaction of two influences on award level decision-making. I instrument for G_{it} with the interaction of: 1) total direct subsidy funding allocated to a firm's industry each year ("technology funding budget"), and 2) the driving distance between the firm's headquarters and the UK's primary grant-making agency, located in London, measured in kilometers ("distance").[31]

The proposed instrument is the *interaction* of these two variables as opposed to using each variable independently as instruments. This allows for the main effects of each variable to be included in the first and second stages as controls. Although the two variables satisfy the relevance condition, they arguably could violate the exclusion restriction on their own. Violations of the exclusion restriction for the interaction term are much less likely, while a compounding effect still satisfies the relevance condition, as discussed below. Controlling for the main effects mitigates the exclusion restriction concerns associated with using the variables independently as two IVs. This follows a strategy first proposed by Card (1995) and used more recently in Bettinger, Fox, Loeb and Taylor (2017).

To justify the use of the interaction term as the instrument, first consider each variable (technology funding budget and distance) on its own as a potential IV. More funding availability through the technology funding budget is positively correlated with the level of funding each winning firm receives. More funding availability for a particular sector translates into higher subsidy awards for firms within the favored sector. Similar measures have been used as IVs in previous studies of innovation grants, such as in Wallsten (2000).

However, the exclusion restriction requires that the relationship between the instrument and outcome measure be caused by only one mechanism: in my setting, the instrument induces firms to obtain larger grant awards, and this affects firm behavior and innovative effort. The funding agencies' decisions regarding which technologies and sectors to support at higher levels are endogenously determined by other governmental policies and priorities as well as market trends. These factors are likely correlated with unobservable firm characteristics that affect R&D decisions.

Distance between the firm and the headquarters of the UK's central department for innovation funding as an instrument has not been used in the innovation literature to my knowledge, but it is inspired by other studies that use distance measures as instruments.[32] Longer distances may

[31] Industry here is defined by the full 5-digits of SICs.

[32] For example, Card (1995) and Bettinger et al. (2017) use distance in their studies on education.

be negatively correlated with grant award levels because it could reduce the number of in-person meetings the firm has with representatives of the agency. In-person meetings need not be part of the application process for this to be relevant—having more meetings over time due to proximity may provide firms with a competitive advantage when it comes to winning grants, as it builds relationships with the funders.

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

If distance or the technology budget is used alone as an IV, the reduced-form estimate will capture the effect of grants but also other plausible mechanisms. To alleviate these exclusion restriction concerns, my instrument is constructed as the interaction of the "distance" and "technology funding budget" variables, capturing a compounding effect. This should be negatively correlated with direct subsidies. If funding availability for a firm's sector increases the award amounts, the effect should be heterogeneous across firms, but the positive effect should be weaker for firms that are located farther away from the grant-making agency. There is more at stake when the grant funding for a firm's industry is higher, so firms that are closer to the grant-making agency will have an even higher incentive to set up meetings and to build relationships when there is more funding at stake.

With the interaction serving as the excluded instrument, the main effects of both variables can be controlled for in the first and second stages of the regression, mitigating the exclusion restriction concerns that otherwise would arise if the variables were used independently as instruments. Of course, causal interpretation still involves an exclusion restriction, but it requires much weaker identifying assumptions than if both variables were used separately as instruments. The interaction IV approach's exclusion restriction only requires that 1) any other mechanism through which firm distance from the agency affects firm behavior is constant over time; and 2) any other mechanism causing firm behavior to differ over time affects firms homogenously with respect to their distance from the agency.

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

The final requirement for the IV to be valid is that it satisfies the relevance condition. Results will be biased if the instrument is weak. The first stage regression results and F-statistics of the excluded instrument presented in Section 4.4 confirm that this is the case. The IV is statistically significant at the 1 percent level across specifications, taking on the expected negative sign, and the F-statistic is high across specifications.

4.4 Main Results

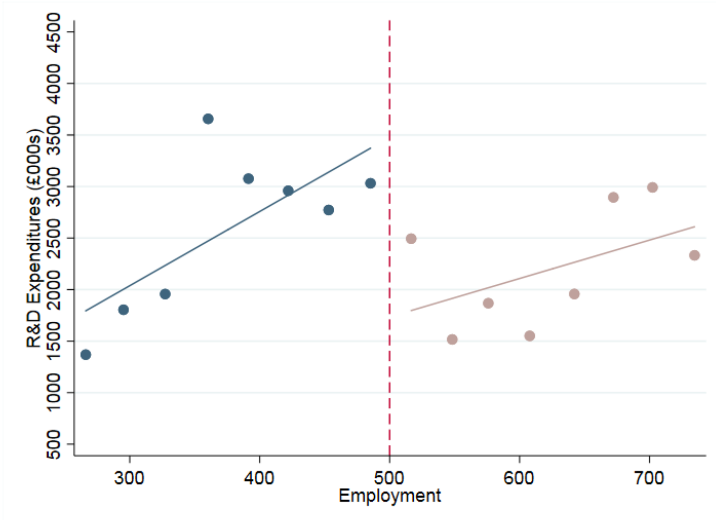
Impact of Increased Tax Credit Rates Only.—Before turning to the interaction of the two types of subsidies, I begin by estimating the effect of higher tax credit rates only. Figure 6 plots average R&D expenditures for evenly-sized groups of firms against total enterprise group employment. Firms with 250 to 750 employees are included for the post-policy period (2009 through 2014). As in Section 4, I assume all firms apply for and receive the R&D tax credit, since I do not observe this in the data, so the effects represent an intent-to-treat.

There is a clear discontinuity in average R&D expenditures at the 500-employee threshold, indicating that the policy has a positive effect. To confirm, I estimate a standard regression discontinuity model (following the form of Equation 1) using the 500-employee threshold for determining treatment status. The results for varying windows around the tax credit generosity threshold are provided in Appendix Table B.9. The results when including linear and quadratic trends of the running variable consistently indicate that there is a positive, statistically significant impact of the increased tax credit generosity in the post-policy period (Panel A) and no statistical discontinuity in the pre-policy period (Panel B). Taking the most conservative case of the linear polynomial specifications, the estimates indicate that firms receiving the more generous tax credits invest about £1.5m more in R&D on average, an effect that is statistically significant at the 5 percent level. This is an increase of 64 percent compared to the average R&D expenditures of the firms in the sample, or a subsidy elasticity of 2.7 with respect to the tax-adjusted user cost of R&D capital.[33] This is a bit higher than other estimates in the literature, however it is almost identical to the recent results in Dechezleprêtre et al. (2016), who find an elasticity of 2.6 when studying the same UK tax credit policy on its own but using administrative data and a different running variable.

This result provides us with two pieces of important information. First, the tax credit policy appears to have large, positive effects on average R&D expenditures for these firms when studying the policy on its own. These estimates ignore the potential interactions of other interdependent subsidies for R&D, however. Second, finding estimates that are nearly identical to those in Dechezleprêtre et al. (2016) provides confidence in the use of the BERD data and employment as the running variable to accurately capture the R&D investments of UK firms in this size range.

[33] I use estimates from the linear polynomial specifications and use the estimated change in tax-adjusted user cost of R&D from Dechezleprêtre et al. (2016) to calculate the elasticity to have a consistent comparison.

Figure 6: Impact of Tax Credit Policy on R&D Expenditures, Larger Firms



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

Subsidy Interaction Effects.—Turning to subsidy interactions, Table 7 provides the main results of estimating the effect of direct subsidies on R&D expenditures by Equation 3 separately on each side of the tax credit generosity threshold. Findings are presented for various-sized windows around the tax credit threshold. The effects of direct subsidies for firms under the tax credit threshold are presented in odd-numbered columns and in even-numbered columns for firms over the tax credit threshold. The final row provides the difference in the direct subsidy estimates below and above the tax credit threshold.

The results indicate that direct subsidies have a positive and statistically significant effect on R&D expenditures in all cases. However, the effect for firms just below the threshold—those receiving more generous tax credits—is significantly *lower* than it is for those above the threshold. In the most conservative case (Columns 3 and 4), the more generous R&D tax credit policy cuts the positive effect of grants in half. The dampening effect of higher tax credits on the marginal effect of grants indicates that the two subsidies are substitutes for these larger firms.[34]

One potential concern is that the estimated effects of direct subsidies are large, which is most likely due to the endogeneity bias of grant funding. However, the scale of the grant effect does not alter the interpretation of the *policy interaction effect*. The *difference* in the grant effect estimates just under and over the threshold—capturing the policy interaction—is consistent across varying sub-samples of data as well as in several robustness checks (see Section 4.6). It is always negative and statistically significant, and this difference is driven by only the discontinuity induced by the

[34]Of course, the findings should be interpreted as a LATEs, given the local nature of the research design.

Table 7: Interaction Effect of Grants and Tax Credits on R&D Expenditures, Larger Firms

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

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

exogenous tax credit threshold.

4.5 Instrumental Variables Approach Results

Table 8 presents results from taking the IV approach described in Section 4.3 with variations in how the IV is constructed. Columns 1 and 2 use the primary instrument, which is the interaction of the firm's distance in kilometers from the funding agency and the total subsidies allocated to the firm's industry each year as defined by the SIC. Columns 3 and 4 use the time to travel (in minutes) rather than distance, and Columns 5 and 6 use total subsidies for the firm's industry based on the first 2 digits of the SIC rather than the full SIC. Appendix Table B.10 provides the first stage regression results, which suggest that the instrument is strongly correlated with the endogenous variable both below and above the threshold. The first stage results are negative, as expected, and statistically significant in all cases.[35]

There are two key takeaways. First, the story is consistent with the OLS results: the impact of direct subsidies is cut in half for firms that benefit from more generous tax credit rates. Second, the first-stage regression results indicate that there is no statistical difference in the effect of the IV on direct subsidies below and above the threshold.[36] This suggests that, even if the IV approach does not fully remove the selection bias (which one may reasonably conclude given that the grant effect estimates actually increase relative to the OLS results), the IV appears to be removing some bias similarly for firms just below and above the threshold. This suggests that the endogeneity of grant funding may be similar for firms just below and above the tax credit threshold, and thus the OLS approach combined with the RDD should be sufficient for examining the subsidy interaction.

[35] The F-statistics for the excluded instrument across the specifications are large, although they are just under 10 in the Columns 5 and 6.

[36] One exception is that the difference becomes statistically significant at the 10% level when using alternative IV #1 in Columns 3 and 4.

Table 8: IV Regressions, Interaction Effect of Grants and Tax Credits, Larger Firms

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

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

4.6 Falsification and Robustness Checks

This section conducts several robustness checks to provide further confidence in the main results. First, I check whether the effect of grants is continuous across arbitrary pseudo-thresholds where there is no difference in the tax credit rates. These results are presented in Table 9. No differences are detected. Second, in Appendix Table B.11, I provide estimates from the OLS regressions with increasing flexibility of the employment running variable up to third degree polynomial controls. The results are nearly identical across specifications, consistently indicating that the effect of direct subsidies is significantly smaller for firms that receive more generous tax credits.

5 Mechanisms

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

Table 9: Pseudo Threshold Falsification Tests, Larger Firms

	(1) Below Threshold	(2) Above Threshold
A. Employment Threshold of 200		
Direct Subsidies (£000s)	2.717***	1.891***
	(0.084)	(0.622)
No. of Observations	5,385	766
Difference at Threshold	**1.317**	
	(0.628)	
B. Employment Threshold of 250		
Direct Subsidies (£000s)	2.058***	2.654***
	(0.370)	(0.360)
No. of Observations	2,011	688
Difference at Threshold	**1.155**	
	(0.516)	
C. Employment Threshold of 750		
Direct Subsidies (£000s)	7.142***	6.615*
	(1.338)	(3.437)
No. of Observations	493	278
Difference at Threshold	**0.143**	
	(3.688)	
D. Employment Threshold of 800		
Direct Subsidies (£000s)	6.465***	8.232**
	(1.175)	(3.854)
No. of Observations	407	276
Difference at Threshold	**0.439**	
	(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.

5.1 Complementarity

5.1.1 Indivisibilities and Easing Financial Constraints

The leading explanation for why subsidies are complements for small firms is that these firms are financially-constrained. Consider the following scenario. A firm that invests in multiple R&D projects has a new idea that it would like to pursue. It applies for and wins a grant that funds 50% of the project's planned expenditures, which increases the firm's total R&D expenditures. The firm continues to claim tax credits on other R&D projects that are not funded by the direct grant. With an increase in the tax credit rate, the firm can now buy a new piece of machinery or equipment for these other projects that it otherwise could not afford because it incurs a large indivisible expense. If this new piece of machinery is also useful for the grant-funded project, it could increase the marginal effect of grants.

Indivisibilities give rise to sizable fixed costs, which may be difficult for financially-constrained firms to fund with non-public sources of capital if the cost of capital is too high. Setting up new laboratories, manufacturing facilities, or office spaces requires large upfront capital. These investment requirements are also indivisible—machines and equipment come in specific sizes and work spaces must be rented for a given time period.

One way of observing whether financial constraints and indivisibilities can explain subsidy complementarity for small firms is to test whether subsidy interactions enhance investments in capital that is indivisible. The FAME data used to study small firm R&D expenditures do not include this information, so I match the Innovate UK data to the BERD and Community Innovation Survey (CIS) databases within the UK Data Services Secure Lab, which provide more detail on the types of innovation investments that firms make (see Appendix A). In Section 4, I corroborated the main findings for small firms with the BERD data, which ensures that interpreting results from studying small firms with these data is reasonable.[37]

I estimate Equation 2 using three dependent variables that proxy for large, indivisible costs: a dummy variable equal to one if the firm made investments in advanced machinery and equipment for the purposes of current or future innovation (from the CIS database), and firm expenditures on land and buildings or equipment and machinery (from the BERD dataset). The results are provided in Table 10. They suggest that subsidy complementarity enhances these expenditures on both the extensive (Column 1) and intensive (Columns 2 and 3) margins. Higher subsidies increases the probability that small firms invest in advanced machinery and equipment by about 52 percent, and there are positive and statistically significant effects on the levels of expenditures.

These results provide suggestive evidence that subsidy complementarities help ease financial constraints associated with large indivisible investments for small firms, as the use of both subsidies increases expenditures that financially-constrained firms may struggle to otherwise finance

[37]Before proceeding, I also re-validate the research design with the CIS data. The typical histogram and McCrary density tests confirm that there is no bunching or increased density of firms just below the small firm employment threshold for these firms (i.e., those that are in the CIS database and also receive Innovate UK grants). I am restricted from providing these plots here because of the small sample, but the log difference is statistically zero.

Table 10: Effect of Subsidy Interactions on Large Indivisible Investments, Small Firms

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

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

privately. To further corroborate this conclusion, I also estimate the main diff-in-disc model on R&D expenditures separately for firms that are under and over the median level of current liabilities, current assets, and firm age. Appendix Table B.12 provides the results. The point estimates, albeit noisy, are much higher for younger firms as well as for those with more liabilities and fewer assets (i.e., those that are more likely to be financially-constrained). This conclusion is consistent with recent findings in the literature that point to grants inducing an additionality effect for small firms, which is associated with overcoming financial constraints (Howell 2017). In the current context, subsidy complementarities—as opposed to increasing the generosity of a single instrument—appear to help firms overcome financial constraints.

5.1.2 Alternative Explanations

R&D Input Relabelling.—One concern often raised in the R&D tax incentive evaluation literature is that higher tax credits provide firms with an incentive to relabel ordinary spending as R&D spending in order to reap more substantial benefits (Griffith et al., 1996). In other words, the estimated positive effects may be a function of firms classifying spending differently as opposed to actually increasing their innovation efforts.

To assess the relabelling hypothesis, I test whether there is a systematic (negative) change in non-R&D inputs that offsets positive changes in R&D inputs. Appendix Table B.13 provides the results from estimating the diff-in-disc model using data from BERD on R&D employment versus non-R&D employment. There is a positive and statistically significant increase in R&D employment (which are large in magnitude compared to the sample mean of the dependent variable), but a very small, negative, and statistically insignificant effect on non-R&D employment. Since labor is the primary R&D expenditure that qualifies for tax credits in the UK, this provides confidence that the subsidy complementarity effect is not simply a symptom of R&D input relabelling.

Learning.—Another potential explanation for finding positive effects for subsidy interactions is learning-by-doing, as knowledge and experience in production can drive productivity growth and increase returns to capital (Lucas, 1988; Arrow, 1995). In the present context, learning-by-doing could be a factor if firms improve in their abilities to apply for, and secure, subsidy funds over time, or if firms learn to more creatively exploit the combination of subsidy schemes. This could explain the results if small firms are more experienced, and thus more acquainted with the subsidy programs, than larger firms. This is not the case. The median ages of small and large firms are 13 years and 27 years, respectively, for the firms studied in this paper.

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

5.2 Substitution

5.2.1 Subsidization of Infra-Marginal Expenditures

The most plausible mechanism for explaining subsidy substitution is that public funds are subsidizing infra-marginal expenditures. That is, they are displacing investments that the firm would have made anyway without the additional funding. Consider the following. Substitution implies that subsidies are interchangeable and used for the same investment types or R&D projects. For example, it may be profitable for a firm to invest in project A if it receives a grant equal to 50 percent of the project costs and it faces an existing tax incentive regime that permits the firm to claim tax credits on the unsubsidized portion of the project. An increase in tax credit rates may induce the firm to spend more on that project, but alternatively, it may keep the project costs fixed if additional expenditures are not required. This increases the total proportion of the project costs that are subsidized as the firm's own investments are replaced with subsidized funds. With diminishing returns, the marginal return to each subsidy type decreases.

One way to evaluate this hypothesis is to estimate the marginal effect of grants on only the firm's internally-financed investments in R&D (as opposed to total R&D investments, which include those financed by public sources and other private sources). Table 11 provides results when using dependent variables that capture firm expenditures on R&D funded by the firm's own funds (Columns 1 and 2) and expenditures funded by other private businesses (Columns 3 and 4). We can see that all of the substitution is accounted for by substitution of the firm's own internal financing of R&D (Columns 1 and 2). A reduction in this firm-financed spending with increases in public funding implies that infra-marginal expenditures are indeed subsidized.

Table 11: Subsidy Interaction Effects by Source of Financing, Larger Firms

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

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

5.2.2 Alternative Explanations

Inelastic R&D Inputs.—Another channel through which substitution could occur is inelastic supply of R&D inputs. If larger firms are constrained (as they could have been immediately following the 2008 economic recession), they may need to temporarily scale-down some projects as they increase efforts in projects tied to subsidy funding. Capital investments and skilled R&D labor may therefore shift from one project to another without increasing the firm's net innovation output.

For an inelastic supply of inputs to explain the findings, the substitution effect should not persist over time (Lach 2002). I estimate Equation 3 for firms under and over the tax credit generosity threshold using only later years in the sample, omitting the years just following the 2008 financial crisis. Appendix Table B.14 provides the findings when using data from only years after 2010 (Columns 1-2) and after 2012 (Columns 3-4). The substitution effect indeed persists. This suggests that the inelasticity of R&D inputs is an unlikely explanation for the substitution behavior.

R&D Input Relabelling—Section 5.1.2 discusses how one form of R&D input relabelling can explain complementarity. A different form of relabelling can also explain substitution. The tax credit in the UK only applies to non-capital expenditures on R&D, which are largely comprised of labor costs. With increased tax credit rates, firms therefore have an incentive to relabel capital R&D expenditures as non-capital R&D expenditures. The total amount of R&D spending reported will remain the same when this occurs. However, the marginal return to grants will decrease because total subsidy levels increase.

For this to explain the results, we would expect to find positive effects of subsidy interactions on non-capital R&D expenditures that offset the negative effects of subsidy interactions on capital R&D expenditures. In fact, though, estimating these effects shows that all of the substitution actually occurs through non-capital R&D expenditures (see Appendix Table B.15). Input relabelling is therefore unlikely to explain the substitution effects.

Political Capture and Information Asymmetries.—A final channel through which substitution of subsidies could occur is related to the objective function of the funding agencies. Grant-making agencies often face political pressure to successfully allocate funds. This can distort preferences in favor of projects that are most likely to succeed, but these projects are also most likely to be privately profitable (and thus pursued by the firm even without the subsidy). As such, public funding could displace private spending that would have occurred even without the subsidy.

Similarly, even if funding agencies are indeed seeking to fund marginal projects, they are unlikely to fully observe attributes that determine whether certain projects will be successful and thus profitable. The firm has better insight regarding inputs like management quality. The informational asymmetry between firms and the funding agency also can lead to the subsidization of infra-marginal projects.

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

6 Discussion: Policy and Economic Growth Implications

The main policy implication of this paper is that accounting for subsidy interactions can substantially increase the effectiveness of public spending on R&D. Policy interactions should not be ignored when designing R&D policy, as they can either undermine or enhance efficiency. In the UK context, increasing tax credits for larger firms that already receive grants crowds out private spending, which suggests that subsidy rates are too high for these relatively larger firms. On the other hand, subsidies are sub-optimally low for small firms. While innovation is already under-provided by markets in the presence of knowledge spillovers, it is even more under-provided where there are increasing returns (Jaffe, Newell and Stavins 2005), just as increasing returns more generally imply that an industry is under-expanded compared to the optimal level of production. Subsidies should increase in the degree of increasing returns (Jaffe et al. 2005). It might be that higher lump-sum subsidies—such as in the form of grants—could moderate the degree of increasing returns due to the presence of fixed costs. This, in turn, could lower the optimal R&D tax credit rate.

Policymakers may also wish to consider the mix of subsidy types and the innovations that they induce when aiming to drive economic growth, since the impact of R&D investments on long-run productivity and growth depends on the composition of research (Akcigit and Kerr 2018; Akcigit et al. 2017a; Segerstrom 2000). Whether public policies such as R&D subsidies drive growth hinges upon two key characterizations of the returns to subsidies and the economy (Segerstrom 2000): 1) whether the subsidies promote horizontal or vertical innovation activities, and 2) which type of innovation is the stronger engine of economic growth in regards to being more profitable and conducive to advancing technological change. The predictions of Segerstrom (2000) state that R&D subsidies increase the long-run rate of economic growth if the subsidies promote the type of innovation that contributes more to productivity and growth.

How do subsidy interactions impact the *types* of innovations that emerge? I estimate the diff-in-disc model using dependent variables that capture more detailed information on R&D expenditures and innovation outcomes for small firms (see Appendix Table B.16). The results indicate subsidy complementarity for investments in projects that aim to help the firm enter a new market (Column 1), which could expand the firm's scope, but not for improving the quality of goods and services (Column 2), which could improve the firm's scale of existing outputs. When examining whether the firm reports producing a new or significantly improved good versus process, subsidy interactions result in more goods innovations (Column 3) but not in more process innovations (Column 4).[38]

Taken together, the results suggest that subsidy complementarity drives small firms to increase horizontal innovation efforts as opposed to vertical innovation efforts. Whether this has an enhancing effect on long-run economic growth depends on whether horizontal or vertical innovation is the stronger engine of economic growth. Although growth theory historically focused on frameworks including a single type of innovation, recent work by Akcigit and Kerr (2018) explores heterogeneity along this dimension. They find that just 19.8 percent of aggregate growth is due to "internal efforts" that improve existing product lines, whereas the remaining growth is due to "external efforts" that create new products. Their terminology of "internal effort" is closely aligned with how vertical innovation is defined here, and "external effort" is more closely related to horizontal innovation. In other words, the most recent state-of-the-art modeling suggests that horizontal innovation is the stronger engine of aggregate growth. This implies that, on the intensive margin, subsidy complementarity for small firms has an enhancing effect on long-run economic growth. The implications of subsidy substitution for larger firms is less clear, as there is insufficient data in the CIS to study them more closely.

[38]This effect is not driven by the sample consisting of just a few industries that are just inherently more likely to focus on goods innovations—the sample includes more than 30 SICs.

7 Conclusion

This paper studies how the interactions of tax credits and direct grants for private R&D impact firms' innovation investment behavior. In the UK context, I show that the two subsidies are complements for small firms but substitutes for larger firms on the intensive margin. The effects are significant both economically and statistically: increasing both grant and tax credit rates more than doubles R&D expenditures of small firms, but increasing tax credit rates for larger firms cuts the positive effect of grants in half. Policy interactions also affect the types of innovations that emerge. Complementarity increases small firms' investments in horizontal innovation efforts, which could enhance economic growth in the long-run under certain conditions.

These results have important policy implications, particularly as many countries continue introducing and increasing the generosity of R&D tax credits. Direct grants and tax credits are the two most popular tools that policymakers use to support business innovation. This paper shows that direct and indirect subsidies are interdependent, and thus accounting for interactions in optimal policy design could substantially increase the effectiveness of public spending on R&D. Subsidies for R&D in the UK are currently sub-optimally low for smaller firms whereas providing multiple sources of funding to larger firms is inefficient from the policymaker's perspective.

The findings presented in this paper should be interpreted with a few caveats in mind. First, the estimates are local average treatment effects (LATEs) and thus cannot be generalized to the population of firms. The results and implications are likely relevant in other contexts, given the prevalence of the interventions studied, but extrapolation must be taken cautiously. Second, due to legal limitations related to merging grant recipient and tax credit administrative data, increases in tax credit generosity reflect an intent to treat. This is a reasonable proxy for the actual treatment effect considering the popularity and salience of the tax credit scheme in the UK. However, interpretation should bear this in mind.

Perhaps most importantly, this paper focused on the intensive margin, which is where the UK's tax credits have been shown to matter most. Nonetheless, the subsidy interaction effects and the policy implications that follow ultimately depend on whether the same complementarity and substitution effects also exist on the extensive margin, and if not, whether the extensive or intensive marginal effect dominates.

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A Appendix: Data – For Online Publication

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

A.1 Data Preparation for Small Firm Analysis

Direct Grants for R&D.—To identify firms receiving direct grants through Innovate UK, which are either treated or not treated by more generous grant generosity levels determined by the program's rules, I begin with Innovate UK's Transparency Database. This contains grant information since the program's inception, providing details on the grant amount award, total project costs, grant year, and competition title. I keep only data from 2005 through 2017, since the 2004 and 2018 data are incomplete, and do not include projects that have been withdrawn from the program. Since some firms receive multiple grants from different competitions in each year, I aggregate the data to the firm-year level. The database contains unique company registration numbers (CRNs) so that firms can be uniquely identified.

Firm R&D Expenditures, Employment, and Other Economic Variables.—Firm-level R&D expenditures data are obtained through Burean van Dijk's FAME dataset, which provides detailed data on the accounts of the universe of UK incorporated firms. The dataset as a whole contains company balance sheet and income statement data from annual accounts filed at the UK company registry. With the help of the staff at Bureau van Dijk, I was able to build a database of company accounts for the firm's identified as receiving Innovate UK grants from 2008 through 2017. Most importantly, the FAME data includes information on firm total assets, employment, and turnover. These are the three variables used by Innovate UK (and the HMRC) to determine whether a firm is eligible for more generous grants under the funding rules. I convert the financial variables in FAME into real 2010 terms using the World Bank's CPI indicators for each year. FAME also provides other useful information that I use as controls in some specifications, such as industry, location, and birth year.

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

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

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

A.2 Data Preparation for Larger Firm Analysis

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

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

I start by collecting BERD data from 2008 through 2014 and omit defense-related R&D investments, as these represent a different type of innovation process and such projects likely receive government support in ways that systematically differ from civil-related R&D projects. All questionnaire forms sent to those identified in the stratified sampling include a minimum set of questions on total R&D spending and R&D employment. The largest spenders on R&D receive "long form" questionnaires and the remainder receive a "short form". The short form asks for basic information related to R&D, such as in-house and extramural expenditures and total headcount of R&D employees. The long form covers more detailed information, such as how R&D expenditures are spent based upon capital and non-capital expenditures. Enterprises not included in the stratified sampling, and responses to questions on the long form from firms that were just sent a short form, have imputed values. These are the mean values of the variable as a share of employment in the firm's size band-sector group.

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

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

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

This aggregation process results in only a very small further reduction in the sample size. For instance, for the year 2014, this results in a sample size of 2,497 observations from 2,544 observations. The most restrictive aspect of the data preparation for the sample size is the use of only non-imputed data. The final 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 grant and tax credit generosity level eligibility for the universe of UK firms. This database is also securely held by the ONS and accessed through the UK Data Services Secure Lab. It BSD includes a small number of variables but covers nearly all businesses in the UK. The data are derived mostly from the Inter-Departmental Business Registrar (IDBR) as opposed to surveys, 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 begin by aggregating variables to the enterprise group level. If the observation is missing an enterprise number and does not belong to a larger enterprise group, I use the given observation's values for each variable. There are about 3 million observations per year. The enterprise group numbers are anonymous but unique so that they can be linked to other datasets held by the ONS.

Calculating Travel Distance and Time.—The main instrumental variable used throughout the analysis of large firms is the interaction between a firm?s distance to the UK's primary innovation funding base in London and the total central government expenditures allocated to a firm?s sector in each year. To begin, I obtained a full list of the UK's postcodes and their latitudes and longitudes. I take just the outward code plus the first character of the inward code to identify the postcode's neighborhood (due to limitations on the geocoding package that I use) and average the latitudes and longitudes for each modified postcode. I then find the travel distances, measured in kilometers and driving minutes, of each modified postcode to the London headquarters of the UK's funding agency's latitude and longitude using the georoute package in Stata.

In theory, these distances can be matched to the BSD data, which provides each enterprise group's postcode. However, the distances could not be calculated in the Secure Lab environment, where all other data for this part of the analysis must be analyzed. As such, I obtained special permission from the UK Data Services to import these postcode-distance combinations into the Secure Lab so that they could be matched to rest of the data required for the large firm analysis.

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

Final Data Sample Preparation.—A few final steps are taken to prepare the data for analysis. First, all expenditure and financial variables are converted into real 2010 terms using the World Bank's Consumer Price Index. Observations associated with inactive firms are dropped from the sample, which results in dropping only 72 observations. Observations with internal R&D expenditures about £400 million are omitted as plotting the data illustrated these points as being clear outliers relative to the majority of the data. This drops 354 observations, and I show that the results are not sensitive to the inclusion of these outliers. The final subsample of the data used includes about 2,000 to 2,500 firms per year from 2008 through 2014.

B Appendix: Additional Tables – For Online Publication

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

	Total Assets	Current Liabilities	Total Proposed Project Costs	Avg. Grant Amt. in Competition
	(1)	(2)	(3)	(4)
1[employment < 50]	9.83	6.65	724.17	98.36
	(10.10)	(8.14)	(843.1)	(135.5)
Employment * 1[employment < 50]	-0.11	0.12	22.1	-0.9
	(0.45)	(0.29)	(36.52)	(4.95)
No. of Observations	1,146	1,138	1,148	1,148

Notes: Dependent variables are other observed covariates. Total assets and current liabilities are in millions of GBP and others are in thousands. Firms with less than 100 employees are included. First order polynomials of the (centered) running variable (employment) are included separately for each side of the threshold. Standard errors are clustered by industry. Asterisks denote *p <0.10, **p <0.05, ***p <0.01.

Table B.2: No Difference in the Discontinuity in Covariates, Small Firms

	Total Assets	Current Liabilities	Total Proposed Project Costs	Avg. Grant Amt. in Competition
	(1)	(2)	(3)	(4)
1[year = post 2012] *1[employment < 50]	-51.44	-29.63	-538.8	1335.77
	(31.72)	(22.65)	(533.36)	(1280.62)
1[year = post 2012] *1[employment < 50] *employment	-0.22	-0.15	-13.22	39.47
	(1.13)	(0.65)	(12.90)	(51.45)
1[employment < 50]	45.51	26.61	538.17	-184.62
	(30.43)	(21.77)	(532.11)	(185.48)
No. of Observations	1,146	1,138	801	1,148

Notes: Dependent variables are other observed covariates. Total assets and current liabilities are in millions of GBP and others are in thousands. Firms with less than 100 employees are included. First order polynomials of the (centered) running variable (employment) are included separately for each side of the threshold. Specifications also include dummies for size threshold, size threshold by centered employment, treatment year (equal to one if the year is post-2012), and treatment year by centered employment. Standard errors are clustered by industry. Asterisks denote *p <0.10, **p <0.05, ***p <0.01.

Table B.3: Sample of UK Policies Providing Benefits for Smaller Firms

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

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

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

	Wide Window (< 100 Empl.) (1)	Midrange Window (10 to 90 Empl.) (2)	Narrow Window (20 to 80 Empl.) (3)
Panel A: Pseudo Tax Credit Change in 2013			
1[year = post 2013] *1[employment < 50]	1764.46	1746.35	475.69
	(1538.58)	(1702.22)	(1857.30)
1[year = post 2013] *1[employment < 50] *employment	3.9	77.01	80.37
	(27.81)	(71.09)	(72.56)
Panel B: Pseudo Tax Credit Change in 2014			
1[year = post 2014] *1[employment < 50]	2384.77	1868.39	730.62
	(2280.14)	(2281.65)	(2536.74)
1[year = post 2014] *1[employment < 50] *employment	-19.94	32.98	54.39
	(29.47)	(56.79)	(78.32)
Sample mean for dependent variable	£1,283.54	£1,408.98	£1,458.59
No. of Observations	197	156	124

Notes: Robustness and falsification tests regarding the year of the tax credit rate change. Standard errors are clustered by industry. Asterisks denote *p <0.10, **p <0.05, ***p <0.01.

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

	Drop Fewer Outliers (1)	Drop No Outliers (2)	Quadratic Polynomials (3)	Cubic Polynomials (4)
1[year = post 2012] *1[employment < 50]	2257.92*	2136.76*	2104.01**	2003.94**
	(1142.99)	(1150.98)	(757.88)	(821.70)
1[year = post 2012] *1[employment < 50] *employment	17.18	13.12	40.72	50.89
	(24.69)	(24.47)	(36.03)	(38.98)
1[employment < 50]	-1111.9	-1059.62	-940.12	-1267.73
	(888.45)	(893.07)	(972.73)	(1390.14)
No. of Observations	218	221	197	197

Notes: Dependent variable is total R&D expenditures (£000s). Columns 1-2 drop fewer outliers in the sample selection. Columns 3-4 use higher order polynomials of the running variable. All other controls are otherwise the same as in the baseline regressions. Firms with fewer than 100 employees are included. Standard errors are clustered by industry. Asterisks denote *p <0.10, **p <0.05, ***p <0.01.

Table B.6: Diff-in-Disc Results Using Alternative Data, Small Firms

	(1)	(2)	(3)
Panel A: Effects on Total R&D Expenditures			
	Wide Window (< 150 Empl.)	Midrange Window (120 Empl.)	Narrow Window (10 to 90 Empl.)
1[year = post 2012] *1[employment < 50]	3611.94**	4233.63**	4064.27
	(1297.40)	(1805.51)	(2490.17)
Sample mean for dependent variable	£1,321	£1,217	£1,727
No. of Observations	262	247	149
Panel B: Effects on Privately-Financed R&D Only			
	Internal Finance	External Private Finance	
1[year = post 2012] *1[employment < 50]	4274.08***	-25.08	
	(1455.13)	(41.05)	
Sample mean for dependent variable	£1,089	£61	
No. of Observations	262	262	

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

Table B.7: Falsification Tests for Diff-in-Disc Using Alternative Data, Small Firms

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

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

Table B.8: Direct Subsidy and Outcome Descriptive Statistics, Larger Firms

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

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

Table B.9: Tax Credit Policy Effects Only, Larger Firms

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

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

Table B.10: First Stage Results for IV Regressions, Larger Firms

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

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

Table B.11: Sensitivity of Estimates to Employment Polynomial Flexibility, Larger Firms

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

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

Table B.12: Estimates Below and Above Median of Financial Constraint Proxies, Small Firms

Data Sub-Sample:	Below Median of Financial Constraint Variable	Above Median of Financial Constraint Variable
	(1)	(2)
Panel A: Firm Age		
1[year = post 2012] * 1[employment <50]	2810.66	1081.10
	(1664.57)	(1003.71)
No. of Observations	104	139
Panel B: Current Liabilities		
1[year = post 2012] * 1[employment <50]	-930.62	3138.07
	(2116.19)	(1934.54)
No. of Observations	110	150
Panel C: Current Assets		
1[year = post 2012] * 1[employment <50]	2033.40*	618.40
	(1099.50)	(900.40)
No. of Observations	102	158

Notes: Dependent variable is total R&D expenditures (£000s). Regression estimates are for firms below (Column 1) and above (Column 2) the median firm age (Panel A), current liabilities (Panel B), and current assets (Panel C). All other controls are otherwise the same as in the baseline regressions. Results are noisy but point estimates are much larger for firms that are expected to be more financially-constrained. Firms with fewer than 150 employees are included. Standard errors are clustered by industry. Asterisks denote *p <0.10, **p <0.05, ***p <0.01.

Table B.13: Effects on R&D vs. Non-R&D Employment, Small Firms

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

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

Table B.14: Persistence of Substitution Effect Over Time, Larger Firms

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

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

Table B.15: Effects on Capital vs. Non-Capital R&D Expenditures, Larger Firms

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

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

Table B.16: Types of Innovation Efforts and Outcomes, Small Firms

Dependent Variable:	To Enter New Market	To Improve Goods Quality	Goods Innovation	Process Innovation
	(1)	(2)	(3)	(4)
Panel A: Wide Window (<150 Employees)				
1[year = post 2012] * 1[employment <50]	1.36**	-1.06**	0.71**	0.15
	(0.57)	(0.42)	(0.26)	(0.26)
No. of Observations	137	139	187	181
Panel B: Midrange Window (< 120 Employees)				
1[year = post 2012] * 1[employment <50]	1.51**	01.25***	0.87**	0.03
	(0.68)	(0.43)	(0.28)	(0.29)
No. of Observations	127	129	173	169
Panel C: Narrow Window (10 to 90 Employees)				
1[year = post 2012] * 1[employment <50]	2.12**	-1.46***	0.91***	0.13
	(0.95)	(0.44)	(0.26)	(0.27)
No. of Observations	113	114	153	151

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